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CCAFS impact assessment of national policy engagement in Kenya and livelihood impact of uptake of climate-smart agriculture technologies and practices

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About CCAFS

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Abstract

The study assessed the impact of CCAFS engagement at policy and household level in Kenya. Specifically, the study assessed the extent to which CCAFS engagement contributed to the observed changes in terms of shaping policy and CSA coordination among others. At the household level the study assessed the factors influencing uptake of CSA practices among smallholder farmers and the subsequent impact of the CSA practices on household dietary diversity, value of household livestock holding and household assets and per capita monthly expenditure as well as GHG emission. The study used a mix of qualitative and quantitative approaches. Specifically, key informant interviews, focus group discussions, observation, and cross-sectional data from household interviews. The study also used econometrics techniques such as the inverse probability weighting regression model, instrumental variable (IV) and Lewbel's heteroscedasticity based IV approach were used to assess the impact at household level.

The study revealed that CCAFS interventions have led to development of a range of policies aimed at promoting CSA. In effect several counties have developed county policies on climate change, some have established climate change units and climate change fund all aimed at promoting CSA. All counties have also mainstreamed climate change into their development plans. However, apart from the multi-stakeholder platforms, the coordination of CSA practices from the national government to the county government has been weak. The overall adoption of CSA practices among farmers in Kenya was estimated at 53.4% with crop management practices being the most adopted at 60.9%. At the household level, the choice of CSA practices among smallholder farmers was found to be influenced mainly by age, sex, marital status, household size and education of household head. The choice of CSA practices is also influenced by smartphone ownership, residential status (i.e. whether native or immigrant), training on CSA, provision of input subsidy by counties, past experience of hailstorms/insufficient rains, visit by agricultural extension officers, knowledge on CSA and whether a household is a crop farmer. Other factors that were found to influence the choice of CSA practices were household monthly income, and household access to credit. The choices of the type of CSA practices adopted were found to be mainly dominated by males.

All the three empirical approaches employed in the study revealed that uptake of CSA by smallholder households increased household welfare measured in terms of per capita monthly household expenditure by about Ksh. 9000, increase household savings (total value of livestock holding) by Ksh. 8.9 million, increased food security as proxied by household dietary diversity index by about 28 percentage points while it reduced GHG emission by about 1.9 million metric tonnes. This implied that adoption of CSA practices meets the dual objective of achieving food security/improving farmer welfare and combating the effects of climate change. A number of policy recommendations are also highlighted.

Keywords

Agriculture; climate change; food security; climate-smart agriculture; impact assessment.

About the author

Boscow Okumu is an experienced economist with a demonstrated history of working in the Kenyan government (at national and devolved levels). He has over ten years of experience in monitoring and evaluation of government policies, development of indicators, M&E frameworks at preparation of progress reports at national and devolved levels of government.

Contents

Chapter one

1.0 Introduction and background

Arid and semi-arid lands comprise about 13.6 million square kilometers of Sub-Saharan Africa (SSA) and support about 290 million people (Notenbaert et al. 2013). Due to depletion of water resources, it is estimated that one in every four people might suffer from extreme water scarcity by 2025 (see Nikolaou et al., 2020). Subsequently, the proportion of arid and semi-arid lands (ASALs) in Africa is expected to increase by between 5% and 8% by 2080 (Collier et al. 2008). ASALs are the most affected by climate change and variability due to high dependence on rain fed agriculture and the increasing experiences of severe temperature and unpredictable and erratic rainfall posing a threat to food security and rural livelihoods (Ching et al. 2011; Campbell et al., 2016; Lewis, 2017; Williams et al. 2017; Fadairo et al. 2019).

Agriculture is the mainstay of most SSA countries (Adhikari et al. 2015, Martey et al. 2021). The most vulnerable sectors to the effect of climate change are crops, livestock, and fisheries (Sere et al.1996). These sectors account for about 60% of Africa labor force therefore at the greatest risk of climate change (Collier et al. 2008). The SSA region also coincides with areas of low food security and high prevalence of poverty (Collins-Sowah, 2018). Smallholder farmers have therefore been the greatest casualties of climate change since they have low resilience to climate shocks due to inadequate resources, safety nets, inadequate access to financial services, and lack of alternative sources of livelihoods (Campbell et al. 2014; Collins-Sowah, 2018; Tibesigwa et al. 2020). They are also often faced with low agricultural productivity and low transformation of the food system (Martey et al. 2021). In the face of climate change and variability, balancing the food demand and supply requires a significant effort to achieve the multiple goals of agricultural adaptation to climate change shocks, reduction of GHG emissions and increasing agricultural yield as well as improving household welfare and increasing household savings (see Fischer 2018; Amadu 2020).

Reducing the vulnerability of smallholder farmers to the effects of climate change and variability and strengthening their adaptive capacities have therefore been the priority of most developing countries in an effort to ensure food security and improving livelihoods of locals especially smallholder farmers (Lipper et al. 2018). Climate Smart Agriculture (CSA)[1] is one such intervention that can enable the achievement of such multiple objectives (FAO, 2018; Lipper et al., 2014). CSA is also critical to the realization of the United Nations (UN) Sustainable Development Goals (SDGs) on elimination of hunger and addressing climate change in low- and middle-income countries (FAO, 2018; IPCC, 2018).

Within the East African region, challenges facing agricultural systems include: inadequate productive land, degradation of land, soil water and other ecosystems; economic barriers such as lack of access to inputs, markets, capital, credit and finance; poor infrastructure; rising land prices, inadequate investment in labor and lack of financial capital and land fragmentation. These factors have not only significantly limited productivity of the agriculture sector but also affected the adoption of CSA practices especially in east Africa of which Kenya is not an exception (Lipper et al. 2014). This is because most CSA practices require intensive labor and financial resources rendering them unaffordable for most smallholder farmers (see Amadu et al., 2020; Bell et al., 2018; Brown et al., 2018).

Moreover, approximately 95% of the food in the East African region is produced under rain fed agriculture (Njeru et al. 2016). In Kenya for instance, the erratic rainfall patterns, continuous rise in temperature experienced with episodes of droughts and floods is a clear evidence of climate change (GOK 2010). Kenya being predominantly reliant on rain-fed subsistence agriculture, it is more vulnerable to the effects of climate change variabilities particularly changes in temperature, precipitation patterns, and extreme weather events. Most smallholder farmers in Kenya also depend on agriculture for their livelihoods (Ochieng et al. 2017). Therefore, to cushion them from the effects of climate change, building their adaptive capacity and resilience is critical. However, this is highly dependent on their ability

[1] Climate Smart Agriculture is an approach that guides actions needed to transform and reorient agriculture systems to effectively support development and ensure food security in a changing climate. It aims to sustainably increase agricultural production and incomes, build resilience of agricultural systems to climate change and minimize GHG emissions (Lipper et al. 2014; CCAFS and Verhagen et al. (2014) also defines CSA as integrated approach to achieve food security in the face of climate change, while also mitigating climate change and contribute to other development goals.

to cope with the impacts of weather shocks, disasters and capacity to absorb the impact of and recover from the shock (Wineman et al 2017; Wekesa et al. 2018).

It is against this backdrop that the Food and Agriculture Organization (FAO) launched the concept of Climate Smart Agriculture (CSA) to guide the management of agriculture, achieving food security and combating the effects of climate change (FAO 2010; FAO, 2013; Verhagen et al. 2014; Arslan et al. 2014; Kabubo-Mariara, 2015; Lipper et al., 2018). CSA concept seeks to: sustainably increase food security through increases in agricultural productivity and incomes; building resilience and adapting to climate change; and reducing greenhouse gas emissions (mitigation) (see Scherr et al. 2012; Collins-Sowah 2018; Lipper et al., 2018). Therefore, to transform the agricultural systems and make them more productive and resilient while minimizing GHG emissions under changing climate, CSA presents the best opportunity for transforming and uniting agriculture, development and climate under common agenda through economic, environmental and social integration (Collins-Sowah 2018). In this study, we consider CSA practice as farming practices that farmers adopt to enable them adapt to the negative effects of climate change and variability in order to improve farm productivity and profitability such as mulching, use of drought resistant varieties, use of weather forecast, and crop diversification among others.

1.1 The study Context: Background of CCAFS interventions in Kenya

Agriculture sector in Kenya contributes about a third of the GDP and about 60% of export earnings (KNBS 2020). It is therefore highly likely to be most affected with climate change and variability since the sector is more reliant on rain-fed agriculture. To address the increasing challenge of global warming and declining food security, the CGIAR Research Program on Climate Change Agriculture and Food Security (CCAFS) has been working with the Kenyan government since 2011in providing technical input into policies and frameworks on climate change in relation to agriculture practices. Through the engagement, CCAFS working with other CGIAR centres contributed to the development of the National Climate Change Response Strategy (NCCRS), the National Climate Change Action Plan (NCCAP) and the Climate Change Policy, and the Kenya Climate Smart Agriculture Strategy (KCSAS) and the related Implementation Framework (KCSAIF). CCAFS has also guided local and international development organizations on focusing their agriculture work under the CSA approach as well as influencing the investments and activities of various stakeholders such as the World Bank, SIDA, UNDP, EU, GIZ, FAO, AGRISS, World Vision, IFAD, and USAID and other NGOS such as Islamic Relief, catholic Relief Services, CARITAS, One-Acre Fund and Red Cross among others.

In collaboration with research organizations, local communities and Non-Governmental Organizations (NGOs) as well as government extension officers, CCAFS has been testing a range of interventions in Climate Smart Villages (CSV) in Kericho, Makueni and Kisumu Counties. This was with aim of identifying steps that smallholder farmers can take to adapt their agricultural practices to secure dependable food supplies and livelihoods while decreasing greenhouse gas emissions or increasing carbon sequestration. The activities include participatory evaluation of multiple stress tolerant (drought, disease, pests) crop varieties and targeting small ruminant resilient breeds for climate change adaptation and improved feeds

CCAFS along with Biovision and the Climate Change Unit within the Ministry of Agriculture, Livestock, Fisheries and Cooperatives (MOALFC), has also been helping launch the CSA multi-stakeholder platform (MSP) that brings together organizations to share information and coordinate activities on CSA, with the aim of helping them to report on CSA progress effectively and accurately to various national and global processes. As a result, many organizations are now using CSA approaches when working with farmers in Kenya. A World Bank assessment of the county risk profiles revealed that Kenyan smallholder farmers lack inputs, irrigation and markets. The farmers are also more vulnerable to climate change and variability since they are more reliant on rain fed subsistence agriculture. The situation across counties is also very heterogeneous calling for county specific interventions. The Kenyan government therefore established the Kenya Climate Smart Agriculture Project funded by the World Bank. The project aims at increasing agricultural productivity, building resilience to climate risk among small scale farmers and providing an effective response in the event of a crisis or emergency[2] although not all counties are covered by the project.

2 https://ccafs.cgiar.org/research/results/county-level-climate-risk-profiles-guide-usd-250-million-investment-kenya#.Xwbo0NycHIV

In addition, at the county level, a CCAFS-funded project led by the Alliance of Bioversity International and CIAT is developing county risk profiles that may also be informing county development plans or other work at the county level. Subsequently, some counties have been able to: establish Climate change units (e.g. Thara Nithi, Homa Bay and Kakamega among others); develop policies and bills/Act (e.g. Tharaka Nithi) to address climate change issues; establish climate fund (such as Isiolo and Tharaka Nithi among others); mainstream climate change into County Integrated Development Plans (CIDPs) and spatial plans and implementation of green initiatives such as solar street lighting, energy efficient cook stoves and climate smart agriculture.

CCAFS, ICRAF, ILRI and CIAT have also been instrumental in the development of Kenya's climate smart agriculture Framework Program (CSA-FP). The program aimed at guiding investment into climate resilient and low carbon agriculture. By mid-2015 the CSA-FP was integrated into Kenya's Intended National Determined Contribution (INDC) submission to the UNFCC. The aim of the INDC is to reduce the country's greenhouse gas emissions by 30% by 2030 relative to a business-as-usual scenario of 132 Mt CO2eq.[3] This was the outcome of a CCAFS led process on "Taking Forward Kenya's NCCAP 2013-2017". The meeting also created a momentum for implementation of the agriculture priority actions in the NCCAP (2018-2022).[4] More recently, CCAFS analysis supported Kenya's State Department for Livestock to increase its understanding of livestock GHG mitigation options, leading to prioritization of efficient livestock production in Kenya's updated NDC submitted to UNFCCC in December 2020.

CCAFS has also been working with the Government of Kenya through the Ministry of Agriculture, Livestock and Fisheries (MoALF) to discuss and take forward priority actions for the agriculture sector identified in the NCCAP (2018-2022). In the dairy sector, Kenya is leveraging on climate finance to promote sustainable development. A meta-analysis of Nationally Appropriate Mitigation Actions (NAMAs) was conducted to identify best practices. Subsequently, climate smart feeding and husbandry practices were then disseminated to

3 https://ccafs.cgiar.org/outcomes/kenya-integrates-climate-smart-agriculture-its-intended-nationally-determined

4 https://cgspace.cgiar.org/bitstream/handle/10568/67906/07outcomecase.pdf?sequence=6

600,000 with 25% being women farmers from a variety of dairy organizations5. It was envisioned that the climate smart actions in the dairy sector could be scaled up to reach 1.8 million households, decreasing the country's emission by 3.3 % of its 2010 emissions while sustaining 180,000 jobs in the sector and improving smallholder incomes by USD 1000-2000 per year6.

In partnership with East Africa Dairy Development (EADD) program and ILRI and ICRAF, Heifer international has been working with 200,000 farmers to improve dairy production and provide access to markets. The main aim of the EADD launched in 2008 in Kenya was to assist 179,000 smallholder farmers owning less than 5 acres of land to participate profitably in the dairy industry. Its major focus was on improving food and nutrition security, increasing farmers' incomes and facilitating access to markets (Nyasimi et al. 2014). The EADD also adopted climate smart agriculture as an objective based engagement with CCAFS scientists, and mounting evidence that better feeding using fodder banks, improved pasture species, planted legumes and crop by products and manure management can contribute to reduction in GHG emission and improved income for farmers7. Heifer international also partnered with the CCAFS funded Standard Assessment of Mitigation Potential and Livelihoods in Smallholder systems (SAMPLES) project EADD and adopted CSA intervention in the new phase of the program. CCAFS scientists have also been engaging with FAO of the UN at an EADD site in Kenya (Bomet, Nandi and Elgeyo Marakwet counties) to estimate GHG emission and productivity of dairy systems8.

Programs such as Kenyan TV show "Shamba Shape Up" have also been instrumental in Kenya by supporting smallholder farmers make over their farms by providing help with recurrent agricultural challenges such as pests and diseases, lack of water and crop production among others. The show has dedicated to CSA up to 35% of total programme time the number of viewers per month is over 9 million, 42% of which have adopted new

5 https://ccafs.cgiar.org/outcomes/scaling-climate-smart-dairy-practices-kenya-through-nationally-appropriate-mitigation

[6] https://ccafs.cgiar.org/outcomes/scaling-climate-smart-dairy-practices-kenya-through-nationally-appropriate-mitigation

[7] https://ccafs.cgiar.org/research/results/east-africa-dairy-development-program-adopts-climate-smart-agriculture#.XwcIodycHIV

[8] https://ccafs.cgiar.org/research/results/east-africa-dairy-development-program-adopts-climate-smart-agriculture#.XwcIodycHIV

practices[9]. Some of the successful case studies in Kenya that have been identified by Nyasimi et al. (2014) are: East Africa Dairy Development Project that adopt a value chain approach in tackling risk management and climate variability; Drought tolerant maize and water efficient maize to increase crop resilience to drought and increase productivity; and Africa Risk Insurance Mechanism, the agro-dealer Development programme, Programme for Africa Seed Systems (PASS) that adopts risk management practices that generate and disseminate agro-advisory services-weather information, insurance, micro-finance, credit and access to markets.

1.2 Rationale of the Assessment and Research Questions

Kenya is currently implementing its third Medium Term Plan of Kenya Vision 2030 and counties are in their second-generation County Integrated Development Plans (CIDPs). These plans have been aligned to international obligations and development agendas that Kenya is party to such as: The United Nations Agenda 2030 for Sustainable Development Goals and AU agenda 2063, climate change (United Nations Convention on climate Change- UNFCCC) among others. The plans seek to address the effects of climate change on agricultural systems through development and implementation of strategies for adaptation and mitigation including early warning, early preparedness, response and improved climate Smart Agriculture technologies and practices and better land management. At the local level, the Kenya Vision 2030 seeks to have a climate-resilient and low carbon sustainable agriculture that ensures food security and contributes to national development goals through: addressing vulnerability due to changes in rainfall and temperature, extreme weather events, and unsustainable land and water management and use; Reducing GHG emissions from agriculture; Establishing enabling policy, legal and institutional frameworks for effective implementation of climate-resilient and low-carbon sustainable agriculture; and Minimizing effects of underlying cross-cutting issues such as low human resource capacity and lack of finance (CCAFS EA Strategy 2019-2021; GoK 2017). Food and nutrition security is also one of the “Big Four” Agenda pillars aimed at fast-tracking the realization of the Vision 2030 and SDGs goal 2.

[9] https://ccafs.cgiar.org/research/results/tv-show-helps-mobilize-east-african-farmers-adopt-climate-smart-agriculture#.XwcFAdycHIV

However, although CCAFS has had over ten years engagement with the Kenyan government at both national and county level, the impact of this initiative at policy and household level has not been determined. Although studies by Nyasimi et al. (2014) singled out some successful selected interventions, none has been proved successful empirically. This is despite the significance of the concept in ensuring food and nutrition security in Kenya, one of the pillars of the “Big Four” Agenda. Further, despite the multiple benefits of CSA and the various interventions by state and non-state actors under various initiatives, there is still a dearth of evidence on the impact of the intervention on shaping policy and coordination efforts. There is also lack of evidence on farmer’s incentives and conditioning factors that influence the uptake of CSA practices as well as the impact of the interventions on the pillars of CSA at household level. It is therefore not known if these interventions have improved household welfare, food security or resilience of households or even reduced household vulnerability and simultaneously reducing GHG emissions. There is also a dearth of evidence on the extent to which CSA policies and practices have addressed issues of gender, and youth or disparities by agro-ecological zones.

Most of the studies in Kenya have been selective quantitative and descriptive case studies with different methodological approaches making comparison difficult (see Nyasimi et al. 2014; Chesterman et al. 2015; Radeny et al. 2018; and Wekesa et al. 2018). The outcome measures have also been varied and subjective. The existing evidence are also hampered by selection bias and endogeneity concerns. The methodological approaches have also been mixed with some studies using individual specific CSA practices or index of CSA practices making comparison difficult. In addition, most quantification of impact is based on country studies or local administrative units while traditionally managing climate risk has been the responsibility of households. Notably, despite the increased promotion of CSA technologies, there is still limited consensus on the effectiveness of existing CSA practices. Little is also known about the links between CSA and livelihood diversification strategies and climate resilience in vulnerable settings. Moreover, most studies even in Africa have not been able to explicitly link CSA adoption with policy intervention and the associated impact on for instance food security, household welfare, household savings and GHG emissions.

The current two-tier system of governance in Kenya also makes the promotion of CSA practices feasible since extension services/agricultural services have been devolved a departure from prior system of governance where agriculture was centralized. In addition, to the best of our knowledge, there has not been any assessment conducted at national and devolved level on the effect of the CCAFS interventions at policy level on adoption of CSA practices and on the household level outcomes.

Moreover, due to the mixed results, the linkage between CSA adoption and household food security, welfare and GHG emission still warrant further investigation to provide policymakers and development practitioners with relevant information. For instance, there is very little evidence demonstrating whether the adoption of CSA by smallholder farmers in Africa and especially Kenya is welfare enhancing. As a result, most donor funded projects and policy interventions in the region are fervently endorsed based on weak evidence (Tibesigwa et al. 2020). The diversity and heterogeneity in terms of climate and agricultural practices among counties in Kenya also warrants a comparative analysis.

The assessment, therefore, seeks to respond to these knowledge gaps by addressing the following questions: i.) What changes can be observed in relation to the objectives of CCAFS's activities in Kenya especially on CSA policy and implementation? (ii) To what extent has CCAFS engagement contributed to the observed changes in terms of shaping policy and CSA coordination efforts? (iii) What might have happened without the engagement of CCAFS and its CGIAR partners? (iv) What factors influence the uptake of CSA practices/technologies? (v) What factors influence the choice of CSA practices among smallholder farmers? (vi)What is the effect of the CSA practices on Household food security, income, yield, resilience and vulnerability? (vii) Are there unintended impacts? What mechanisms delivered the impact, and what lessons can we learn from this process? What are key contextual features for these mechanisms?

We contribute to the scant literature on CSA by looking at a portfolio of CSA practices and management options on production risk focusing on 22 counties evenly distributed across the six agro-ecological zones in Kenya and assessing impacts of adoption of the same on a vector of outcome variables namely: household food security, household welfare (per capita monthly expenditure), household savings (value of livestock holding), and value of household assets and GHG emissions in metric tonnes. We extend the literature further by using novel econometric approaches: weighted probability regression model, instrumental variable regression model and Lewbel's heteroscedasticity based instrumental variable approach that address potential selection bias and endogeneity concerns. The remainder of the paper is organized as follows. Chapter two presents a review of related literature, chapter three presents the methodological approach and chapter four presents the results and discussion while chapter five presents the conclusion and policy recommendations.

Chapter two

2.1 Related Literature and CCAFS impact pathways

This section presents a review of related literature on CSA at policy level and at household level as well as CCAFS envisioned impact pathways. The review looks at both theoretical and empirical literature.

2.1.1 Policy Level interventions related literature

A number of studies have tried to explore the contribution of climate smart policies at different levels. According to McCarthy et al. (2018) climate smart policies encourage improved decision making, enhance resilience and adaptive capacity to changing agro-climate conditions and adoption of best feasible technologies, improve input use, and post-harvest practices at farm level. Some of the climate smart policy scopes that can amplify CSA adoption include: Cash transfer programmes, subsidized index-based insurance (livestock and crops), and input subsidy programme. However, although these policies were meant to reduce poverty and increase food security and therefore aimed at reducing economic vulnerability rather than climate vulnerability, they have proved effective in managing climate risk and potentially mitigating effects of climate change (See Caron et al. 2018; Collins-Sowah 2018).

According to Lipper et al. (2018), improvement of climate change and agricultural governance through better coordination and institutional strengthening is key for success of CSA. This is based on the premise that institutional environment can incentivize farmers and increase their ability to invest in agricultural practices and adapt to climate change (McCarthy et al. 2018). McCarthy et al. (2018) also posit that institutional innovations at macro and farm level such as "climate smart" extension programs, full spatial coordination among farmers to deal with associated externalities and social safety nets etc. can support CSA technology adoption. Caron et al. (2018) identified a number of areas of institutional support that are critical for uptake of CSA technologies and management practices. These include: provision of attractive and viable financial and risk management tools; increasing information dissemination needed for smallholders to increase knowledge and technical skills; enabling farmer groups and cooperative access high value markets; and protecting livelihood of smallholder farmers through safety nets in the event of adverse weather. Collins-Sowah (2018) also highlighted the importance of private and public sector partnerships in expansion and improvement of the supply chain of credit and farm level inputs and outputs.

The promotion of CSA is also heavily reliant on collaboration with research institutions to ensure farmers get access to the right technologies and information as well as the know how in the use of these technologies. In addition, conducive environment, macroeconomic stability, assurance of peace and security functional markets and incentives can also stimulate CSA adoption (see Westermann et al. 2015; Collins-Sowah 2018). Access to information has also been shown to be critical factors in adoption of CSA technologies. Provision of weather forecast information can serve as an early detector of growing conditions and can help farmers adjust to planting seasons by adjusting planting dates hence improved agricultural productivity, manage risks and take advantage of favorable weather conditions (see Hansen et al. 2011; Thornton et al. 2018). Moreover, integrating agricultural advisory services, input markets with tailored climate services which provide new information to complement and extend farmers knowledge can empower smallholder farmers and reduce climate uncertainty (CIAT 2015). Lipper et al. (2014) also posits that CSA promotes coordinated actions by farmers, researchers, private sector, civil society and policymakers towards climate-resilient pathways through: building evidence; increasing local institutional effectiveness, fostering coherence between climate and agricultural policies and linking climate and agricultural financing.

Nyasimi et al. (2014) also highlights that: multi-stakeholder collaboration is key to sharing information and addressing similar agricultural problems at different levels (national and regional); governments must support and enable growing private sector by providing appropriate markets, infrastructure and policies; an enabling institutional and policy environment is needed that supports agricultural research and education oriented to farmers' needs as well as the diversification of farming systems; climate change adaptation strategies must be appropriate to women's capacities and needs; and that responsive national and regional markets should be promoted to provide access to credit and finance schemes to enable farmers to invest in new and emerging climate smart technologies. They also revealed that CSA practices need to provide incentives and market opportunities that will transform subsistence agriculture into profit led enterprises and that the practices should support the development of enterprises that offer diverse and sustainable source of income to help cushion families through difficult periods such as droughts and floods.

2.1.2 Household level interventions related literature

At the household level, a number of studies have tried to tease out the drivers of adoption of CSA practices as well as their impact using different approaches. For instance, Wekesa et al. (2018) sought to determine the drivers of adoption of CSA practices and the effect of adoption of CSA on household food security among smallholder farmers in Teso North Sub-County, Busia County of Kenya. Using the Principal Component Analysis and the multinomial endogenous switching regression model, they found that adoption of CSA packages was mainly influenced by gender, farm size and value of productive assets. They also found that the impact of CSA was greater for households that adopted various categories of CSA practices. Weak technical and institutional capacity, inadequate resources, high cost of adoption of technologies are some of the barriers to smallholder household adaptation (see Mayaya et al. 2015). They also revealed that delays in meteorological information, lack of subsidies, costly farm inputs, inadequate credit facilities, poor access to agricultural extension service and agricultural markets, limited farm size and inadequate labor have hindered uptake of adaptation strategies.

On the other hand, Makate et al. (2019) also found that multiple adoption of innovations is influenced by access to credit, income, information, and education level and land size owned by the household.

Another study by McCord et al. (2015), investigated factors contributing to varying levels of crop diversification and implications for crop production across an upland-lowland gradient on Mt Kenya's northwestern slopes a semi-arid irrigated agricultural system. Using regression analysis on household level survey data, they found that household income, field size, exposure to extension services, and suitability of environmental conditions are related to likelihood of smallholder crop diversification. Crop diversification is also a strategy that households may employ to reduce vulnerability to external stress factors, such as climate change (Lin 2011). A number of studies have also shown that adoption of CSA technologies like crop diversification are determined by land suitability, income level, risk avoidance, contact with extension officers and social norms (see Cutforth et al. 2001; Di Falco et al. 2003).

According to Nyasimi et al. (2014), to build smallholder farmers resilience to climate change, there is need for a greater adoption of integrated CSA technologies. While analyzing the uptake and impact of CSA technologies on food and nutrition security, income and asset accumulation in climate smart villages in Kenya, Radeny et al. (2018) found that there was an increase in uptake of CSA technologies and innovations across the CSVs coupled with improved agronomic and livestock management practices. In addition, they found that adoption of crop and livestock related CSA technologies and practices have positive and significant impact on food security, income and asset index. Specifically, their study revealed that adoption of multiple stress tolerant crop varieties increased household dietary diversity by up to 11 percentage points, increased asset index by up to 60 percentage points and more than doubled household income per adult (equivalent $ 140). The adoption of small ruminants also increased household dietary diversity scores by up to 10 percentage points and increased asset index by up to 51 percentage points.

A review of existing evidence of different sustainable land management practices aimed at increasing and stabilizing crop productivity in developing countries by Branca et al (2011), revealed that soil and climate characteristics were key in interpreting the impact on crop yields and mitigation of different agricultural practices and that technology options which are most promising in enhancing food security at smallholder level are also effective on increasing system resilience in dry areas and mitigating climate change in humid areas. In Bangladesh, Mendola (2007) assessed whether adoption of modern seed technology by resource poor farmers improve their income and decrease the propensity to fall below the poverty line. Using non-parametric propensity score matching analysis, they found robust positive effect of agricultural technology adoption on farm household wellbeing suggesting that there is a large scope for enhancing the role of agricultural technology indirectly contributing to poverty alleviation. Mukankusi et al. (2015) evaluated 21 bean varieties bearing different characteristics with over 300 farmers in replicated trials in the first season of 2012 and two seasons of 2013 respectively. They found that breeders and farmers look out for similar traits with yields being the major driver, and in most cases end up with the same result with few discrepancies.

A recent study by Teklewold et al. (2020), investigated the effects of a combination of climate smart agricultural practices on risk exposure and cost of risk using panel data from the Nile Basin of Ethiopia. Using multinomial treatment effects framework by controlling weather variables for key stages of crop growth, they found that adoption of combinations of practices is widely viewed as a risk reducing insurance strategy that can increase farmers' resilience to production risk. They also reject the hypothesis of equality of weather parameters across crop development stages. Using data from Niger, Asfaw et al (2016) assessed the determinants of adoption of agricultural technologies under climate risk and evaluated their impact on food security. Using the multivariate probit and instrumental variable techniques to model adoption decisions and their impact, they found that adoption of modern inputs (inorganic fertilizers and improved seeds) and organic fertilizers is positively associated with crop productivity and crop income. They also found that weather variability, household wealth, education, labor, distance to the nearest market and distance to nearest extension centres were some of the determinants of the type of practices adopted.

In Tanzania, Tibesigwe et al. (2021) found that multi season cropping systems are highly productive and earn more revenue and are less likely to be affected by rainfall variability. On the other hand, Amadu et al. (2020) found that adoption of CSA practices led to a 53% increase in maize yield in Malawi. In China, Liang et al. (2021) found that adoption of both adaptive and mitigatory CSA practices increases rice yield and rice net income. However, while exploring the impact of CSA adoption on nutritional outcomes in Ethiopia Teklewold (2019) found that farmers adopting a combination of CSA practices were more nutritionally secure than those adopting a single practice. Habtewold et al. (2021) found significantly higher impact in several deprived households while assessing the impact of CSA adoption on multidimensional poverty. The impact was mainly through increased income or consumption via the non-food expenditure pathway. Using matching methods and simultaneous equations, Ogada et al. (2020) found that adoption of multiple stress tolerant crops improves household income which in turn improve household asset accumulation. They also found that adoption of improved livestock breeds significantly reduces household income and attributed this to the possibility of income being invested in the form of livestock rather than household assets a more resilient measure compared to investment in domestic household assets.

Crop rotation and zero tillage has also been found to improve technical efficiency while crop insurance had no significant effect on technical efficiency (see Tong et al. 2019). On the other hand, concurrent adoption of conservation agriculture, stress adapted legume varieties and draught tolerant maize were found by Makate et al. (2019) to have greater dividends on productivity and income than when considered individually. They however found that the impact of multiple adoption of practices are heterogeneous across geographical regions and by gender.

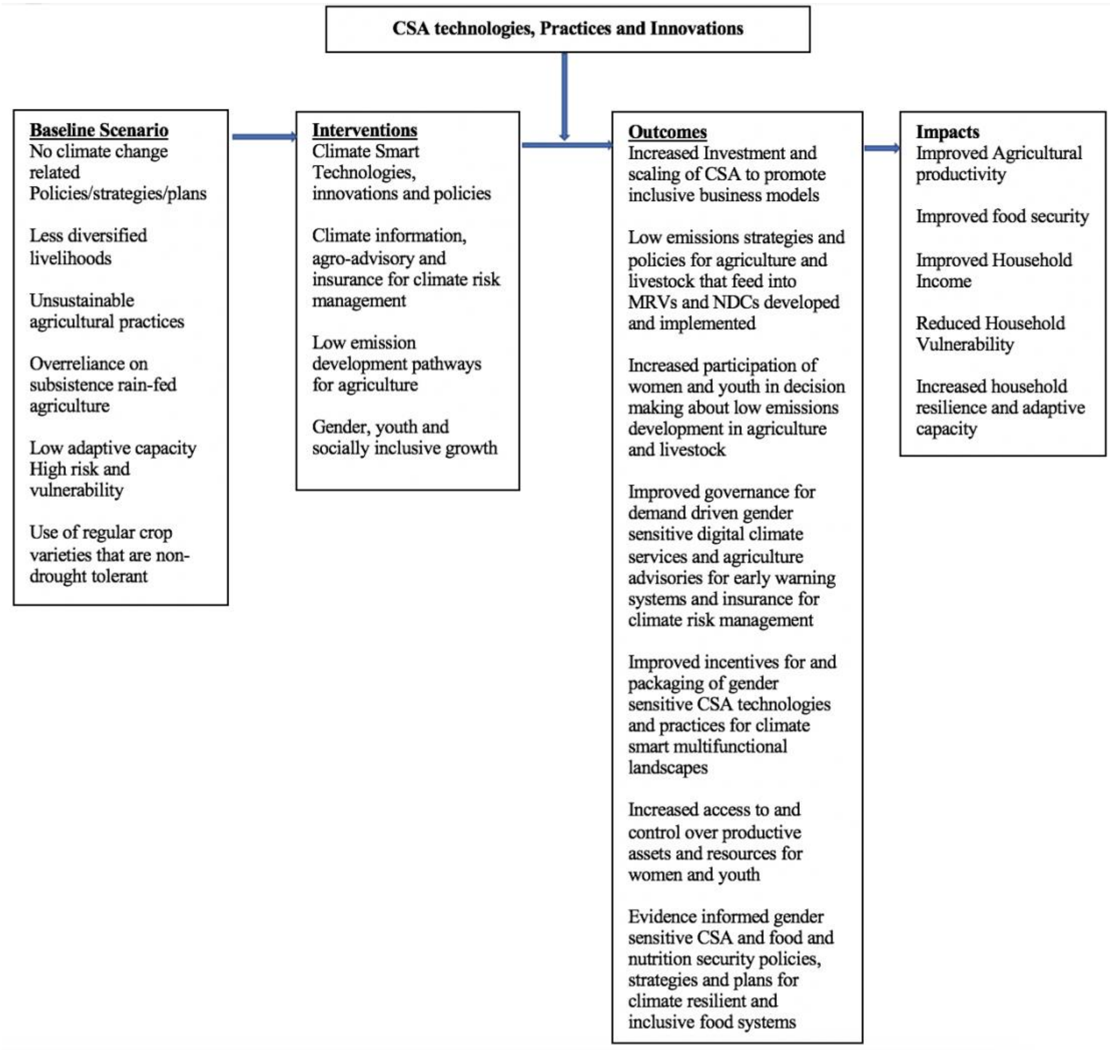
While assessing the impact of row planting as a climate smart agriculture practice on welfare of rural household in Ethiopia using PSM and semi parametric local instrumental variable version of the generalized Roy model, Fentie et al. (2019) found that adoption of row planting technology had significant positive impact on per capita consumption and on crop income per hectare. Plot level characteristics were also found to influence household's adoption decisions (Manda et al. (2016). They also found that adoption of a combination of sustainable agricultural practices raises both maize yields and income of smallholder farmers.

Overall, although there is a good number of studies on climate smart agriculture in Kenya, a general overview reveals significant differences in applied definition, contextual factors and methodological approaches as well as definition of variables making comparison difficult. Most of the studies are also single case studies. Most of the studies have also looked at the effects of isolated CSA practices on welfare (see Tong et al. 2019; Ogada et al. 2020; Fentie et al. 2019). However, farmers may adopt a portfolio of CSA practices (Teklewold et al. 2019; Makate et al. 2019; Amadu et al. 2020) to maximize on agricultural production and improving their welfare. In addition, most of the studies have focused on single outcomes mainly food security or welfare proxied by various methods hence prone to measurement errors. This study therefore contributes to this literature using 22 counties in Kenya as a case study. Further, the study extends the literature through assessment of the dual impact of adoption of a portfolio of CSA practices on a vector of outcome variables linked to household livelihoods and GHG emissions. This is done by first exploring the impact of employing mitigatory and adaptive CSA practices and further explore the potential synergies between adaptation and mitigation practices.

2.2 CSA impact pathways

The main objective of CCAFS is to contribute to a climate resilient nation which is food and nutrition secure and that has equitable access to livelihood opportunities for all while improving natural resource systems and ecosystem services. This is to be achieved through promotion of climate smart agriculture to increase carbon storage in agricultural systems as well as reducing GHG emissions from food systems and agricultural value chains to mitigate climate change and supporting enabling policies and increased investments in agriculture and natural resource management. As per the CCAFS 2017-2022 phase II proposal, the aim was to: reduce poverty by having 11 million farm households adopt CSA practices by 2022 through this action and policy engagement; improve food and nutrition security by providing climate lens on the actions and interventions and using its climate smart village approach to test approach in an integrated manner; and improve environmental health through technical development of mitigation options in collaboration with CGIAR research programmes.

The promotion of climate smart agriculture was aimed at addressing the persistent constraints and challenges in agriculture through innovative technologies and practices, policies and enabling environments and conducive investments (CCAFS EA2019-2021). The major areas of action even in the CCAFS EA-2019-2021 strategy revolves around the four areas proposed in CCAFS phase II proposal borrowed from Lipper et al. (2014) which are mainly: building evidence; developing capacity of institutions and services; coordinating climate and agricultural policies; and stable strategic investment to reach scale. The impact pathway builds on the CCAFS phase II proposal and is further elaborated as per Figure 1 showing the baseline scenario and the stated interventions based on the four key interconnecting interventions (namely: testing, evaluating and increasing access to and promotion of climate smart technologies, innovations and policies; climate information, agro-advisory and insurance for climate risk management; working with governments, private sector and other non-state actors to raise awareness on low emissions development (LED) systems in crop and livestock sectors; and gender, youth and socially inclusive growth. Figure 1 presents the CCAFS envisioned impact pathways).



Source: CCAFS EA 2019-2021

Chapter three

3.0 Methodological framework

The overall objective of the assessment is to assess how CCAFS engagement with the government has helped shape policy and CSA coordination efforts as well as an understanding to what extent these policy changes have influenced farmers' practices across the agricultural value chain. In order to assess the progress and achievements of the programme in addressing the objective, identify and document lessons and provide recommendations, both qualitative and quantitative approaches were employed.

A thorough analysis of the theory of change in the CCAFS EA strategy 2019-2021 and the CCAFS phase II Proposal was done in order to derive full understanding of the intervention. The theory-based approach helped examine how the program interventions were to deliver outcome and impact and then assess where the links at various results levels are weak or missing. The study therefore adopted a combination of quantitative and qualitative approaches. Specifically, a desk review of relevant documents was conducted followed by Key Informant interviews (KIIs), Focus Group Discussions at household level as well as observations during the fieldwork. Quantitative data was collected at household level through household administered questionnaires. Finally, the causal claim about the impact of the process linking program interventions with final outcomes was derived from theory, perceptions of stakeholders (mainly policy makers and key informants) and the household level analysis results.

3.1 Desk Review

The first step involved an extensive desk review of the CCAFS program documents, CCAFS relevant publications, outcome case studies, the CCAFS EA strategy in order to understand the CCAFS Theory of Change and how CCAFS's engagement in Kenya was expected to influence various policies and frameworks on climate change, agriculture and CSA. This also involved a review of the various government publications on climate smart agriculture e.g. NCCRS, NCCAP, KCSA, KCSAIF. CIDPs for the 22 counties were also reviewed to assess the level of mainstreaming of climate change. The findings from the review guided development of research tools for use at household and policy level. The study also examined how CCAFS, NAMA, CIAT, ICRAF and the World Bank KCSAP have influenced CSA at national and county level. The review findings were used for comparative purposes, establish lists, patterns and trends. All such data/ records have been appropriately referenced in the study report.

3.2 Key Informant Interviews

In depth Interviews with Key Informants: Virtual interviews (via Zoom, Webex and Teams) were conducted with government actors at national and county levels. This involved interviews with Climate Change Directorate at the Ministry of Environment, Climate Change Unit at MOALFC, KCASP and Agriculture Sector Development Strategy Programme (ASDSP) officers at county level and head of any existing county climate change unit and department of agriculture. Finally, interviews were also held with ILRI as one of the non-state actors involved in CSA and climate change issues[10]. The interviews were meant to explore and validate findings from the desk review. The interviews covered CCAFS engagement with government in development of the CSA strategy and implementation framework as well as in preparation of agriculture and gender submission for UNFCCC negotiations. Interviews were also conducted with relevant CCAFS scientists and partners as agreed by the CCAFS team. The aim of the KIIs was to find out policy maker's views, opinions, knowledge, experiences with the CCAFS's influence on CSA in Kenya. Thematic analysis was used to interrogate the themes emerging from the interviews. The findings from the KII informed the refinement of the final household questionnaire. A summary of the KIIs for policy interview is presented in Table 1.

Table 1. Key Informants from state and non-state actors interviewed

Entity	Target KII
State Departments	Ministry of Environment and Forestry, Climate Change Directorate; climate change unite- State Department for Crop Development; Climate Change Units -State Department for fisheries; Climate change desk officer:-The National Treasury and Planning; State Department for Livestock, KFS, KALRO and NEPAD
Council of Governors	Agriculture desk officer
Counties	
1. Narok, 2. Trans Nzoia, 3. Laikipia, 4. Homa Bay, 5. Tharaka Nithi, 6. Kakamega, 7. Isiolo, 8. Kilifi, 9. Nyeri, 10. Nandi, 11. Vihiga, 12. Busia, 13. Nakuru, 14. Nyandarua, 15. Baringo, 16. Kajiado, 17. Kitui, 18. Nyamira, 19. Migori, 20. Kwale, 21. Marsabit, 22. Meru.	Director Agriculture (crop development), Director Livestock, Director Fisheries, Director Environment, local Chiefs, village elders
Non-State Actors	ILRI (CCAFS)

[10] There was no conflict of interest since the interview was just to gain understanding on the interventions ILRI is implementing at either national or devolved level.

3.3 Focus Group Discussions

Focus Group discussions were held in groups of 6-8 with strict adherence to COVID1-19 Ministry of Health guidelines. For these FGDs *appreciative inquiry* and *more significant change* approaches were used interchangeably. The FGD tried to tease out the various CSA practices that farmers were engaged in, the organizations that have been supportive among others. The FGDs constituted about 70 percent female since most farmers available at home in the villages were mostly female.

3.4 Household/farmers level- Quantitative Analysis

At the household level, quantitative data was analyzed to explore the drivers of adoption of CSA technologies and practices and the impact of adoption on various welfare indicators. The study adopted a three-step strategy in meeting the study objectives. The first step was to estimate the determinants of household choice to adopt CSA practices and then proceeded to assess the drivers of adoption of CSA practices by the different management practices. The third step involved estimating the impact of adoption of CSA practices on a vector of outcome variables conditional on CCAFS policy intervention.

3.4.1 What influences the adoption of CSA practices

In this study adoption of CSA practice implies the application or use of various CSA practices in agriculture. In this study 26 different CSA practices grouped into different management practices were considered. The first step was to determine an approach to consolidate the CSA practices and determine who is an adopter and who is non adopter. An index for adopters of CSA practices was constructed using principal component analysis (PCA). PCA was used to assign weights to the selected indicators. This is because simple allocation of equal weights is too subjective (Gbetibouo et al. 2010). Thus,

Given $x_1, \dots., x_n$variables, PCA extracts the orthogonal combinations of variables that capture common information to form uncorrelated principal components i.e.

$$p_1 = a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n$$
$$p_2 = a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n$$

$$p_n = a_{n1}x_1 + a_{n2}x_2 + \cdots + a_{nn}x_n$$

where $p_1 \ldots p_n$ are the first to n[th] principal components; a_{ij} are the factor loading "weights" indicating the level of variance of original variables explained by each factor. p_1 explains largest share of variation, p_2 the largest of the remaining variance, and so on. The weight for each variable thus varies between -1 and +1, with the sign (+ or -) of the variables denoting the direction of relationship with other variables used to construct the respective index. The PCA score was also constructed for each of the groups of CSA practices namely: crop management practices; land management practices; farm risk reduction practices; soil and water conservation practices; and livestock management practices. The study then constructed a dummy variable taking on one if PCA score was greater than zero and equal to zero if PCA score was less than or equal to zero.

In order to assess the drivers of adoption of CSA practices, the household decision to adopt CSA practice (D_i), we estimate the empirical model specified by

$$D_i = \Phi(\beta_0 + \sum_j^k \beta_j \boldsymbol{Z_j}) + \varepsilon \tag{1}$$

Where $\Phi(.)$ is the standard normal cumulative density function, β_j are the parameters to be estimated and Z_j is a vector of household characteristics hypothesized to influence household choice of CSA practices. The model was estimated using a probit specification based on the distributional assumption about the error term (ε) (see Wooldridge 2010).

3.4.2 Estimating the Impact of CSA adoption

Analytical Framework

The framework is grounded in Roy (1951) occupational choice model. We assume that households decide whether to adopt CSA technologies or practices that maximizes their utility. If a household expect to benefit from adopting the CSA practice then we assume they will adopt the practices. Assignment to treatment is therefore non-random. Define V_{ij} the utility of household i=1 2……N in treatment regime j= {0, 1}, with 1 representing adoption of CSA technologies and 0 otherwise. Therefore $D_i = 1$ if $V_{i1} > V_{i0}$. Similarly, Y_{ij} is defined as a vector of potential outcome variable (i.e. total value of household assets, total value of livestock holding (savings), and per capita household monthly expenditure, GHG emission, and household food security (Household dietary diversity)). Where Y_{i1} is the potential outcome for adopters of CSA practices and Y_{i0} is the potential outcome for non-adopters of

CSA practices. The difference between Y_{i1} and Y_{i0} can therefore be used to measure the differential impact on the outcome variables.

According to Rubin (1973), program impact is the difference between the observed and the counterfactual outcome. The main challenge is that counterfactual is not observable, and an individual cannot be in both states at the same time. A quasi-experimental approach is therefore more appropriate for identifying the counterfactual given that adoption of CSA practices is non-random. Controlling for adoption decision is therefore important to tease out the impact of CSA adoption. We consider that differences in potential outcome variable for CSA adopters can be due to unobserved heterogeneity, reverse causality, simultaneity, and measurement errors. Failure to distinguish between the causal effects of adoption of CSA practices and effect of unobserved heterogeneity may lead to misleading conclusion and policy implication.

In this study we adopt a range of identification strategies to estimate the impact of CSA adoption. As a baseline specification, we estimated the OLS model followed by the Inverse probability regression model to handle the selectivity issues then extended the empirical approach to various specification of instrumental variables methods to control for endogeneity bias. The choice of IV model was informed by intuition, economic theory, literature and the test for endogeneity and its source. A rejection of the null hypothesis of exogeneity warrants conclusion that IV models can be used to identify the treatment effect. However, since the strength or credibility of exogeneity test also depends on the strength of the instrument used, OLS and IV estimates should both be presented when exogeneity is not rejected (see Bellemare et al. 2017). To assess the robustness of the IV estimates, the analysis was extended further by use of the Lewbel's Heteroscedasticity based instrumental variable approach that uses internally generated instruments in the absence of plausible instruments (see Lewbel 2012). The IV models are also preferred due to their suitability and superiority to other models.

3.4.3 Inverse Probability Weighting Regression Adjustment (IPWRA) model

The household decision to adopt CSA practices is assumed to depend on the anticipated benefits. The latter are proxied through the following outcomes: total value of household assets, total value of livestock holding, and per capita household monthly expenditure, GHG emission, and household food security (Household dietary diversity). The main interest is the average treatment effect on the treated (ATT). However, it is not possible to estimate the ATT by simple difference of the above metrics because it is not possible to observe what the metrics would have been without adoption of CSA practices (treatment) and because assignment to treatment is also nonrandom. Quasi experimental approaches therefore suffice. We solve the self-selection and missing data problem using the inverse probability weighting regression adjustment model. The IPWRA is a two-step procedure in the first step propensity scores are estimated to create the weights and defined overlaps between comparison and control groups then the weighted regression is estimated.

Analytical framework

Assuming that the distribution of the outcome variable is independent of treatment i.e. adoption of CSA technology, given a vector of covariates, a propensity score matching estimator for the average treatment effects on the treated can be estimated. The intention of matching is to create a control group of non-CSA adopters that is similar as possible as to adopters of CSA technologies although the groups may be significantly different. The inverse probability weights mimic the matching intuition through reweighting to make the adopters and non-adopters distribution look as similar as possible. However, identification of average effect of adoption of CSA within this framework requires both strict ignorability of treatment, $(Y_{1i,}Y_{01} \perp D_i \backslash P(X_i))$ and the propensity score overlap, $0 < P(X_i) < 1$ (Dehejia et al 2002; Rosenbaum et al 1983). The other assumption results in common support in which similar individuals have positive probability of being both adopters and non-adopters of CSA technologies (Heckmann et al. 1999). The study therefore adopts the IPW regression model following () where the probability is derived from a logit model in line with the propensity scores.

$$Prob\ (D_i = 1|X_i) = \wedge\ (X\Gamma) \qquad (1)$$

The explanatory variables in the model include farm, household and demographic characteristics. We also include explanatory variables such as distance to the market among others. Based on the results from the above model, the IPW regression adjustment model was applied, where the propensity scores are used to reweight the data. In the model, propensity scores are first estimated to create the weights and define overlaps between comparison and control groups and then the weighted regression is estimated (Cameron et a l. 2005; Wooldridge 2003).

The treatment effects inverse probability weighted regression adjustment (IPWRA) estimates the average treatment effects on the treated and the potential outcomes from observable data by IPWRA coefficient. The IPWRA estimators use weighted regression coefficients to compute average of treatment level predicted outcomes where the weights are estimated inverse probabilities of treatment. The advantage of IPWRA estimators is that they have the double robust property since the teffects IPWRA accepts a continuous, binary, count, fractional or nonnegative outcomes and allows multivalued treatment. The estimated model is therefore a standard treatment effects regression, wherein the outcome variable of interest is regressed on the treatment together with controls from the propensity score regression, see equation (1) and related text (Cameron et a l. 2005; Wooldridge 2003; Dehejia et al 2002; Heckmann et al. 1999; Rosenbaum et al 1983). This is done to control for any covariate imbalance that could influence the estimates.

3.4.4 Instrumental Variable Regression Model

The OLS model measures only the magnitude of association, rather than the magnitude of causation which is critical for policy analysis. Subsequently, if the adoption of the CSA practices was random then the study would have adopted the standard ordinary least squares (OLS) regression model. However, for the OLS model to yield consistent estimates adoption of CSA practices must be independent, conditional on the covariates, of the unobservable that impact on the outcome variables. Moreover, even if the distributional assumption concerning the error term is correct, adoption of CSA practices will not be independent with the error term conditional on the covariates if adoption of CSA practices is influenced by unobservable attributes such as income level, inert ability, and access to information etc. issues concerning endogeneity of CSA adoption therefore arise.

The identification of the causal effect through nonlinear functional forms is however plausible, but more robust estimates can be archived through non-trivial exclusion restriction or instrumental variable (Heckman and Navarro-Lazano, 2004; Heckman Vytlacil, 2005; Pearl. 2000). The validity of the IV approach relies on two assumptions. First, the instrumental variable must be correlated with the treatment (adoption of CSA practices).

Second, that the IV must be correlated with the outcome of interest through the IV relationship with the treatment that is the IV must not have direct effect on the outcome (see Angrist et al. 1996; Wooldridge 2010). In this study we adopt the use of long-term historical climate variables that capture rainfall and temperature patterns as identifying instruments (see Asfaw et al., 2016). Specifically, the study computed a coefficient of variation for ten year monthly average temperature and rainfall for the 22 counties sampled which were used as instruments. The variables were therefore measured at county level. The motivation for choice of instrument is that as farmers form expectations on climatic conditions of their area based on experiences, the instruments are assumed not to affect the outcome variables (food security, household vulnerability and value of livestock holding) directly, but only through the choice of CSA practices. To assess the robustness of IV estimates, the study also use the Lewbel's heteroscedasticity based instrumental variable approach following Lewbel et a. (2012). The analytical framework for the approach is presented in annex 5A.

3.5 Definition and Measurement of Variables

A desk review of the programme documents and government publications helped in identification of the CSA interventions at the devolved level. The study used a range of outcome variables namely; total value of household assets, household per capita monthly expenditure, total value of livestock holding (savings), household food security and GHG emission. Household food security was measured through household dietary diversity which was constructed as an additive index11, while total value of livestock holding was employed as most rural households save their earnings from agricultural crop production in livestock which is also a symbol of wealth in the villages. It therefore serves as a proxy for household savings. Total value of livestock holding were obtained by getting the sum of the current unit price of each animal with number of livestock (goats, sheep, cows, camels etc). This was further guided by the counties identified. Since some households may resort to purchase of household assets after sale of their agricultural produce, we also considered value of household assets. The choice of various outcome measures was due to the heterogenous

[11] This was constructed based on the kinds of food the household consumed in the last 24 hours. The food considered were; vegetables, fruits, meat, banana, orange, eggs, fish, legume, oils, , milk, sweets and spices..

nature of counties. It is important to note that valuation of livestock holding is subjective12. Most households were not able to give exact figures. The prices of the same also varied with season. We therefore decided to use an average estimate to capture both seasons13.

Household welfare is measured by per-capita monthly expenditure[14]. Per capita monthly expenditure was preferred to household monthly income since households are prone to under reporting their monthly income. The income may also have fluctuated given that the interview was conducted during the COVID-19 pandemic period. The choice of per capita expenditure is also easily interpreted and provides information over the consumption bundle that fits within the household budget although this may be affected by micro finance institutions that are enabling easy access to credit facilities among village households or smaller women groups “chamas” (Okumu et al., 2020). Monthly expenditure is also preferred due to ease of recall. The expenditure was aggregated household spending on food supplies, education, farming and livestock, clothing and apparels, medical and other miscellaneous items. GHG emission data was also proxied through average carbon emission in metric tonnes per year from 2010-2018 by county[15]. This therefore implies that each household in a given county takes the GHG emission values for that particular county as they all contribute to the emissions in some way.

The interventions or CSA practices were grouped into five categories namely: crop management practices (Growing drought resistant crops/multiple stress tolerant crops such as sweet potatoes and cassava, Crop rotation, Changing planting dates following rain, Sequential cropping, Multi season cropping, Intercropping); Land management practices (Use of terraces/land contours, Stone gabions, Planting trees on crop land, use of live fences, Adoption of cover crops in farm); farm risk reduction practices (diversified crop/increased

[12] We acknowledge that total value of livestock holding could be subjective compared to use of Tropical livestock units. Moreover, although rural farmers have low literacy levels, they could easily give the market values for their animals hence the errors could be small even if they over priced them.

[13] We noted during the field work that when schools open, the value of livestock is normally very low as most households sell their livestock to take kids back to school. The prices of agricultural produce also tend to be low during harvest season due to high supply hence likely to affect household expenditure.

[14] This was based on the average monthly expenditure for the last 12 months.

[15] https://rainforests.mongabay.com/deforestation/archive/Kenya.htm

range variety of farm crops, irrigation, use of weather forecast (agro-weather information), insurance (crop and livestock insurance)); soil and water conservation practices (planting food crops on tree land/agroforestry, use of mulching, rain and flood water harvesting, application of organic manure, integration of legumes (nitrogen fixers), efficient use of inorganic fertilizers); and livestock management practices (use of plastic silos for post-harvest fodder management, use of muskan milk containers, diversified animal breeds, use of improved livestock breeds, feeds and feeds management/fodder banks).

Other controls were household sociodemographic profiles such as age of household head, gender, income sources, economic activities, farm and contextual variables as well as elevation, soil type, and climatic variables etc. We control for policy level interventions by including dummies for presence of KCSAP project, whether a household was contacted by county on CSA, and whether a household has been trained on CSA practices by the county or any national government institutions or NGOs and also include interaction terms in some models.

3.6 Survey Design and Data Collection Methods

3.6.1 Sampling Design

The study used cross sectional dataset, collected between the months of October 2020 and August 2021. The first phase covered 9 counties between October and December 2020. This was extended to 22 counties between March and August 2021 to increase the sample size. Although the data was collected at two different time periods the two phases could not be significantly different since the seasons are basically same by ecological zones. A multi-stage sampling technique was adopted. At the household level, the sampling frame for this study included farmers, fisher folks and pastoralists in selected counties whether adopting CSA technologies or not. IPW regression model require that both samples must be larger than the sample size suggested by power calculations. Generally, oversampling must be greater for the potential comparison group than for the treatment group (White et al. 2014).

The first step of sample selection was identification of counties. Counties were purposively selected based on the Agro-ecological Zones (AEZs)[16] and regional representation. According to FAO (1996) an Agro-ecological Zone is a land resource mapping unit, defined in terms of climate, landform and soils, and/or land cover having a specific range of potentials and constraints for land use. The AEZs are *upper highlands*, *Upper Midlands*, *Lowland Highlands*, *Lowland Midlands*, *Inland Lowlands* and *Coastal Lowlands*. A list of the AEZs in Kenya and the sampled counties is presented in Table 2.

Table 2. Agro-ecological Zones in Kenya and the sampled counties

Agro-Ecological Zones	Counties	Selected Counties
Upper Highlands	Murang'a, Meru, Nyandarua, Nyeri, Nakuru, Elgeyo Marakwet	Nyeri, Meru, Nyandarua, Nakuru
Upper Midlands	Machakos, Nyamira, Narok, Vihiga, Kisii Kirinyaga, Kiambu, Trans Nzoia	Narok, Trans Nzoia, Nyamira, Vihiga
Lowland Highlands	Laikipia, Uasin Gishu, Nandi, Kericho	Laikipia, Nandi
Lowland Midlands	Tharaka Nithi, Kakamega, Homa Bay, Kisumu, West Pokot, Embu, Busia, Bungoma, Siaya, Migori, Kajiado Kitui, Makueni, Taita Taveta, Bomet	Kakamega, Homa Bay, Tharaka Nithi, Migori, Kajiado, Kitui, Busia
Inland Lowlands	Baringo, Isiolo, Turkana, Marsabit, Garissa, Tana River, Wajir, Samburu, Mandera	Isiolo, Baringo, Marsabit
Coastal	Lamu, Kilifi, Kwale	Kilifi, Kwale

Source: Africa Women Studies Centre/KNBS Baseline Survey on Food security (2013)

Based on the AEZs, a total of 22 counties were purposively identified as a general representation of the Country namely: Kakamega, Busia and Vihiga (Western); Kwale and Kilifi (coast); Tharaka Nithi, Meru, Kitui, Marsabit and Isiolo (eastern); Nyamira, Migori and Homa Bay (Nyanza); Nyeri (Central), Narok, Nyandarua, Baringo Kajiado, Laikipia, Nandi,Nakuru and Trans Nzoia (Rift Valley). The purposive sampling of counties avoided sampling Climate Smart Villages Counties such as Kericho, Kisumu (Nyando) and Makueni (Wote).

[16] An Agro-Ecological Zone is a land resource mapping unit, defined in terms of climate, landform and soils, and/or land cover and having a specific range of potentials and constraints for land use (FAO, 1996)

The second step was determination of number of households per county. A stratified random sampling technique was adopted. This step involved determination of the total sample size for the entire study then using proportionate sampling to determine sample size per county and the second step was to determine the sample size per sub-county (the study sampled at least three sub-counties per county). This was to ensure adequate representation in terms of geographical/climatic conditions and population per county. The third step was to determine the sample size per enumeration area in each sub-county identified. Within each Sub-County, we identified an enumeration area (an administrative location headed by chiefs) and used the list of households at the chief's office to randomly select households into the study.

Temperature and rainfall data were gathered from the climatic data provided by the Climatic Research Unit (CRU) at the University of East Anglia (Harris *et al.,* 2020). The climate data combines data from more than 4000 weather stations around the world and satellite data, to get high-resolution monthly estimates of temperature and rainfall over the period 1901-2020. The advantage of this database is that it is provided at fine spatial resolution (0.5x0.5 degree) grids which allows us to aggregate the data to different geographical levels. Using the county shapefile for Kenya, we extract monthly average temperature and rainfall data between 2011 and 2020 for each of the 22 counties sampled. We used ten-year monthly average rainfall and for temperature, computed the coefficient of variation since variance in temperature or rainfall in the short term is just as important as the mean temperature or rainfall. The paper assessed all the 26 CSA practices identified from the literature.

3.6.2 Sample size determination

First, the sample size must cater for the statistical significance (assumed at 95%, Z=1.96), margin of error (e=2.5%), estimated variance in the population as decimal (p=0.5, q=1-p). Using the statistical sample size formula as proposed by Cochran (1963)

$(n = \frac{Z^2pq}{e^2})$.

$$n = \frac{(1.96)^2(0.5)(0.5)}{(0.025)^2} = 1537\ households$$

Assuming a non-response rate of 20%[17], the final sample size was estimated at (1537/0.80) = 1921 households. This was rounded off to 1900 as it was considered to constitute a significant number of both categories (adopters and non-adopters) into the study for sufficient abstraction from the two groups based on socio economic trends. This was felt would constitute a nationally representative sample and would be proportionately distributed across the 22 counties. Using proportionate sampling the total sample size per county is therefore summarized in Table 3. The table shows that Kakamega county was under sampled this was attributed to the adverse weather conditions that hindered movement and mechanical breakdowns. Some counties like Isiolo and Marsabit were also very vast with sparsely distributed population.

Table 3. Distribution of Households sampled by County

No	County	No of HH	HH Sample proportion	Approximate sample size	Number of Households sampled	Response rate (%)
1	Nyeri	248,050	110	111	85	77
2	Narok	241,125	107	108	85	79
3	Trans Nzoia	223,808	100	100	78	78
4	Laikipia	149,271	66	67	76	113
5	Kakamega	433,207	193	193	74	38
6	Homa-Bay	262,036	117	117	72	62
7	Tharaka Nithi	109,860	49	49	60	122
8	Isiolo	58,072	26	30	39	130
9	Kilifi	298,472	133	133	103	77
10	Nyandarua	179,686	57	70	101	144
11	Nakuru	616,046	197	200	108	54
12	Baringo	142,518	46	60	66	110
13	Nandi	199,426	64	80	92	115
14	Vihiga	143,365	46	70	86	123
15	Busia	198,152	63	70	94	134
16	Nyamira	150,669	48	60	98	163
17	Migori	240,168	77	90	88	98
18	Kajiado	316,179	101	110	72	65

[17] We assumed a non-response rate of 20% due to the COVID-19 pandemic and some cultural beliefs in certain communities. This was done taking into consideration that at some point in time, rural communities were so much hostile to people from Nairobi since they believed COVID-19 was being spread by Nairobi residents. In certain areas especially Marsabit, and Isiolo and part of Kilifi and Kwale counties it was difficult to get responses since most households preferred the husband to be interviewed and at times were never there.

19	Kitui	262,942	84	100	99	99
20	Kwale	173,176	55	70	70	100
21	Meru	426,360	136	150	88	59
22	Marsabit	77,495	25	60	75	125
	Total	**3,126,182**	**1900**	**2098**	**1809**	**86**

Source: 2019 Kenya Population and Housing Census: population by County and Sub-County Volume I, Field data from the 22 counties

3.6.3 Data Collection procedure

A mixed method approach comprising both qualitative and quantitative data collection methods were employed. The use of mixed method approach helps in strengthening and expanding study's conclusion and heightening its validity (Schoonenboom et al. 2017). Household level and policy level data were collected between the months of October 2020 and August 2021. Household surveys were administered to collect data regarding household demographic and socioeconomic profiles, extension and information services, housing sanitation, water and energy, market information services, land ownership and utilization, agricultural activities, household food security, climate and geographic variables. The household survey had duration of approximately 35 minutes. The policy makers' level survey and other non-state actors' survey had duration of 20 minutes. Qualitative data were collected through focus group discussions, in depth interviews with key informants, case studies/stories and field observations during the transect walks. On the other hand, quantitative data were collected through in-depth household interviews with farmers. Approximately three FDGs were held per county comprising of 6-8 persons. The FGDs gave information to strengthen findings from the household's interviews and were mainly qualitative in nature exploring the farming practices and nature of support from national or county government towards promotion of CSA technologies.

Households were randomly selected from the register of households at the chief's office, the chief then designated village elders to take the enumerators and research assistants to the identified households. In case where the household head or an adult were not at home the next neighboring household was selected for interviews. However, this was a very rare occurrence since most rural households were in the farms or at home and in some cases where the household head was not available, the wife was always present. The houses were generally very cooperative in providing required information since the village elders always introduced the teams. It is important to note that some agricultural produce was very difficult to quantify especially at the village level, but much effort was made to make the questions easy. The other challenge was translation of the questions into local language. The village elders however made the task much easy to locals.

At the household level, a total of 1809 households were interviewed from the 22 counties. A distribution of the households by county is presented in Table 3. Data was collected from all households regardless of whether adopter or non-adopters of CSA. Supplementary data on climate change, geographical variables and farm and household characteristics and CSA practices and technologies were also collected from households sampled. The study revealed that various CSA technologies have been widely adopted by households i.e. at least every household adopted a technology. The analysis within the study employed both household level and policy makers' level data. However, information obtained from KIIs, focus group discussions, transect walks and case stories helped contextualize the results.

3.7 Ethics and Approval

Ethics and approval for the study was sought from ILRI Institutional Ethics Committee (**Ref: ILRI-IREC2020-36/1**) and a research permit was obtained from NACOSTI (License No: **NACOSTI/P/21/6864**). Permission was also sought from the county commissioner in each of the 22 counties and local area chiefs. The farmers to be interviewed were asked for their consent first before commencement of the interviews.

Chapter four

4.0 Results and Discussions

This section presents the results of the study including findings from the KIIs with policy makers and empirical results from the household interviews using various approaches. The first section presents a summary of the KII findings followed by summary statistics and then the ordinary least squared, IPW regression model followed by IV estimation model and the Lewbel's Heteroscedasticity based instrumental variable approach respectively (See Lewbel et al. 2012).

4.1 Policy Level interventions: Findings from the KII and FGDs

At the National level the Multi-Stakeholder Platform consisting of government, public, private, research, academia, farmer organizations, CSOs, development partners working on CSA with the Ministry of Agriculture Livestock, Fisheries and Cooperatives (MoALF&C) and Climate Change Unit (CCU) as the coordinating agent has been instrumental in promoting CSA practices at the national level despite the short time. This could be concerning issues of technical and financial support from the various partners in the platform. The KIIs at the national level revealed that a collaboration between CIAT, CCAFS, ILRI, ICRAF and Mazingira Institute and development partners such as GIZ, USAID, JICA, UNDP, FAO, and the World Bank supported various national government departments (i.e. State Department for Agriculture, State Department for Livestock, State Department for Fisheries and Blue Economy and the State Department for Irrigation) leading to production of various policy documents namely: National Climate Change Response Strategy, National Climate Change Action Plan, National Adaptation Plan, updated Nationally Determined Contribution submitted to UNFCCC in December 2020, Kenya Climate Smart Agriculture Strategy, Green Economy Strategy and Implementation Plan, development of UNFCC country positions and submissions on agriculture and gender for the UNFCC. Most of these strategies are disseminated through workshops with county governments who are expected to cascade them further to farmers through Information Education and Communication (IEC) materials, field demonstrations and workshops and sensitization meetings.

Further, the FGDs with farmers, revealed that about a third of the population had heard of CSA or know about CSA. Those who had heard it was mostly through local radio stations, TV programmes and few trainings and workshops conducted mostly by NGOs as well as field demonstrations. In some counties like Narok all the FGDs held revealed that none had knowledge of CSA nor had heard about CSA therefore low uptake of modern CSA technologies. However, this could be attributed to the low levels of education and the pastoralist nature of communities living within Narok. This was also the case in certain sub counties in other counties. This shows that there is need for county specific interventions instead of a one size fits all approach like it is currently.

Most of the state departments have also collaborated with CCAFS in development of climate change policies and plans, capacity building of stakeholders on climate change and participation in UNFCC climate change negotiations. Research outputs from the collaboration between national state departments and research institutions normally inform modelling future scenarios and applying the same for proactive planning such as NDCs and Medium-Term Plans as well as formulation of County Integrated Development Plans (CIDPs). Climate change lenses are also currently applied in research process. The national government has also encouraged involvement of private sector in development of climate change related market information services and products to sustainably transform agriculture through provision of legal and legislative frameworks and support to private sector to develop bankable project proposals. However, a major challenge that has hindered promotion of CSA from the national to the county level is the politics of agriculture as a devolved function and breakdown of the reporting structures from the grassroots to get accurate data.

The KII with national and county government officials also revealed that the collaboration between national and county government is wanting because agriculture is a devolved function. Further, the promotion of national level CSA interventions at county level is implemented through former agricultural officers who were inherited by county government after devolution hence its more of a good will and the officers can refuse since they are now employees of the county. This has made the approach unsustainable. However, the arrangement has somehow worked though when it comes to disbursement of finances for any activity say crop insurance or engagement of communities through workshops, the finances are picked from the national government ministry by a national ministry official who goes to the ground to disburse the funds with support from the county agriculture officer. It was also revealed that the national government is planning to post liaison officers to the county level to handle national government functions. This implies that the coordination arrangement will further be worsened since counties will also be running parallel similar programs. It is therefore evident that there is weak coordination of CSA practices from national to county level and is set to worsen if left unchecked as the national government is unwilling to send funds directly to county governments to support agricultural activities. It was also noted that national government engagement with communities at the county level have often been prone to elite capture where only the elites who access the information frequently attend unlike when its coordinated by counties where county assembly members and ward administrators spread the information across the entire location. This calls for strengthening the Multi-stakeholder Platform to improve coordination of agricultural activities and data flow and accuracy and exploring ways of integrating the two levels of government.

The FGDs with smallholder farmers further revealed that most contact with smallholder households on CSA has been with NGOs (such as CARITAS, RED CROSS, One-Acre Fund, Amiran, Syngenta among others). Although a good proportion have also been contacted by county government officials. County governments have been supportive in some counties by providing subsidized fertilizers and seeds but one has to register. The channel of communication on subsidy provision in some counties is also unclear since most announcements are made at funerals hence most households miss and is also prone to elite capture. There is also no fairness in distribution of inputs (mainly seeds and fertilizers). We witnessed one seed distribution function in Isiolo county during the field work. Some counties also do farm demonstration especially cotton farmers in Homa Bay. Counties like Homa Bay have also benefited from distribution of banana suckers, jembes, pangas, wheelbarrows and championing soil and land conservation through terraces and trenches as well as field demonstrations with support from KALRO and Ministry of Agriculture. It is also important to note that in some sub counties such as Narok, there has never been contact whether with NGOs or either level of government on issues of CSA.

One of the outcomes of the national engagements is the Kenya Climate Smart Agriculture Project (KCSAP)[18]. Out of the 22 counties sampled in the study 10 counties benefitted from the project namely Nyeri, Laikipia, Isiolo, Tharaka Nithi, Busia, Baringo, Nyandarua, Kajiado, Marsabit and Kakamega. Specifically, the KCSAP project promotes the following CSA practices in Kenya: establishment of weather monitoring infrastructure; development of early maturing crop varieties; Sahiwal breed that tolerates most of the diseases suitable for ASALs; fortified for nutrition; feed conservation practices; big data-Kenya agricultural

[18] KCSAP is a 5 year (2017-2022) Government of Kenya project jointly supported by the World Bank under the framework of the Agriculture Sector Development Strategy (ASDS)(2010-2020) and national Climate Change Response Strategy (2010). The project is implemented in 24 counties in the whole country and aimed at increasing agricultural productivity and enhancing resilience/coping mechanism to climate change risks in the targeted smallholder farming and pastoral communities in Kenya. The key components of the project are: upscaling CSA practices; Strengthening CSA Research and Seed Systems; Supporting Agro-weather, Market and Advisory Services; Project coordination and Management; and Contingency Emergency Response.

observatory platform; and provision of weather advisory. All counties have also mainstreamed climate change issues into their plans and policies and most have created climate change fund, climate change units, and climate change Acts/Policies or action plans. A number of counties also have Climate change policy (Tharaka Nithi, Busia, Kajiado, Migori, Vihiga, Marsabit, Kwale, Baringo, Meru, Nakuru and Homa Bay), Climate Change Unit (Tharaka Nithi, Nandi, Marsabit, Busia, Kajiado, Vihiga, Meru, Homa Bay and Kakamega). Tharaka Nithi, Isiolo, Nandi, Busia, Kwale, Kitui and Vihiga have a climate change fund or some were at advanced level of establishing the fund. Some counties such as Tharaka Nithi have Climate Change Act and climate change response strategy.

Although counties were hardly aware of CCAFS they said that most of the practices at the county level were being borrowed from national level implying that without CCAFS most of the policies at national and county levels would not have been in place. The multi-stakeholder platforms have also provided grounds for engagement that have benefited various institutions in diverse ways especially in terms of select projects. Schedule four of the Kenya Constitution highlights that national government will play key role in providing technical support to counties. Therefore, any policy developed by national government they have to support counties to come up with county specific policies on the same and align to the national government policy. This implies that the national policies will also be implemented at the county level. The same happens in all planning documents where the CIDPs have to be aligned to the national plans the Medium-Term Plans (MTPs).

The expectation is that such interventions from national level through counties should trickle down to the household level. However, at the household level, we found that households had stuck to the traditional crop management and land management CSA practices as described in the household level results. The traditional CSA practices in this study refers to those that households have been doing since time memorial for instance use of organic manure, inter cropping, agroforestry, crop rotation etc. The predominant CSA practices that the county governments have been promoting are mainly: minimum tillage; planting drought tolerant crops/early maturing; agroforestry, water harvesting for crop production; irrigated agriculture/solar irrigation; organic farming; crop insurance; and establishment of conservation structures among others. However, despite the promotion of such initiatives, most smallholder households at the county level still practice CSA practices such as;

irrigation from boreholes and rivers, sack farming, use of drought resistant crops, changing planting dates, mixed cropping, manure and fertilizers, terrace and contours, delaying planting due to weather advisory, crop rotation, and tree planting. The most effective CSA practices were mainly; improved variety, on-farm soil and water management, runoff harvesting and conservation agriculture among others in small scale as revealed from the KIIs and FGDs. It was also noted that most farmers did not adopt most of the livestock related practices.

Counties have further been upscaling adoption of CSA practices through capacity building and promotion of CSA technologies, establishing green climate fund, provision of crop and livestock insurance to farmers, research and continuous training of farmers, provision of drought tolerant/early maturing crop variety seeds for bulking, supporting commercial fruit tree nurseries and excavation of water pans for vegetable production through irrigation, sensitization of framers on impact of climate change, support of agro-weather, promotion of climate financing schemes, market and climate advisories, among others. The knowledge on CSA have also been transferred through field demonstrations, workshops/barazas, TV programmes-shamba shape up and provision of IEC materials. The integration of CSA has also been mainstreamed and aligned to the county plans to a large extent in most counties. However, knowledge about the CCAFS is very limited at the county level although most of the county interventions target women and youth groups and strive to ensure that a third gender rule is complied with. National government has also been supporting counties through mainly projects implemented in collaboration with KCSAP, KALRO, CRAL, NARIGP, AFA, AND KMD.

In research, counties have been partnering with various universities such as JKUAT, Meru University, Egerton University, University of Nairobi and Chuka Universities. Other institutions include KALRO, ICRAF, CETRAD, Kenya Seed Company, and Agri Seed Company and national government departments such as State Department for Water, State Department for Interior, State Department for Crops, State Department for Fisheries, National Draught Management Authority, National Environment Management Authority, Kenya Meteorological Department, Kenya Forest Service, Lake Basin Development Authority. Non-state actors such as IFAD, CARITAS, Islamic Relief, Red Cross, Catholic Relief Services, World Bank, USAID, WFP, SIDA, UNDP, EU, SNV, GIZ, FAO, ASDSP II, AGRISS and World Vision have also been supportive in a number of counties.

The study also found that marketing of agricultural produce has remained a major challenge since most smallholder farmers use brokers who exploit them. Other challenges smallholder farmers still face include: price fluctuations, lack of transport and bad roads especially during rainy seasons. Brokers tend to dictate the prices since they most of the time provide farmers with inputs hence once produced they deduct the cost of production when paying farmers. The brokers also tend to dictate the packaging, prices and grading. Another major problem is the influx of cheaper farm produce from neighboring countries such as Uganda and Ethiopia. In addition, at times there are no market and most goods are perishable making them sell them at throw away price. This thus implies that there is need for encouragement of farmers to join cooperatives or marketing societies or to engage in contract farming to get market for their produce hence improve their livelihood. A good experience was in Kabondo Sub county in Homa Bay, farmers indicated that after the CSA training by KALRO they now get bumper harvest. In return the community formed sweet potato CBO (cooperative society) to solve marketing challenges faced by sweet potato farmers in effect over 10,000 farmers are now engaged in sweet potato farming in Kabondo as the market is readily available through the CBO. Overall, despite the challenges in most counties, most farmers agreed that their welfare had improved compared to before training.

On the other hand, in terms of information access, farmers revealed that most agricultural advisory services they received through local radio stations and TV stations and at times farm visits or field demonstrations and group meetings in some counties. Agro-weather information is also often communicated through vernacular radio stations especially during planting season and when the rains are about to fall for farmers to prepare. This information is often about 70-80% accurate and has been useful in giving direction on farming. However, it was noted that counties that do not have access to local radio channels relied on general weather information which is not often accurate as it is not county specific. The early warning advisory have been received positively in most counties and has been helpful in planning. The success of this has been the spread of such information through social media and spread through farmer groups. Some of the challenges that have hampered adoption of CSA in some counties have been lack of knowledge and training on CSA. Counties like Narok wondered that at the moment the produce is moderate yet they have zero knowledge on CSA what would happen if they were empowered with the right CSA skills? Other challenges highlighted by smallholder farmers have been lack of financial resources. It was also noted that there are no agricultural extension services nowadays since most extension services is provided at the shopping centres on so called clinic days. However, not all farmers can afford to go to markets on those days.

From the key informant interviews and FGDs, we can conclude that to increase adoption of CSA technologies at the grassroots, there was need to sensitize farmers on climate change and variability as well as its effects, benefits of CSA adoption, increased demonstration and more investment in extension service delivery, input subsidies, matching grants to purchase farm inputs and organization of farm demonstrations on CSA at the community level. However, this is likely to be hampered with inadequate extension staff and inadequate funds. Counties suggested setting aside at least 10% of the budget towards agricultural extension services.

4.2 Summary Statistics

To determine the adopter of CSA practices, the study used PCA by considering all the 26 indicators for CSA practices. The PCA was preferred to the additive index because it produces a more effective measure by recovering the underlying latent variable (Darnell, 1994). The Kaiser-Meyer Olkin (KMO) measure of sampling adequacy revealed that CSA practices had an overall KMO measure of 0.7 allowing for the use of PCA. The PCA results revealed that the first two components had eigenvalues greater than one dominating in terms of eigenvalues and proportion of variance. The first component also makes more economic sense as it contains positive weights for all the CSA practices evidence of aggregate variation because of variation in adoption levels by households (Fujiie et al., 2005). We therefore classified households based on PCA scores with PCA scores greater than zero as adopters of CSA and those with less than or equal to zero as non-adopters. This revealed that 969 households were considered adopters of CSA practices and 840 households' non-adopters of CSA practices.

Summary statistics of household socioeconomic and demographic profile is presented in Table 4. As expected, per capita monthly expenditure, total value of household assets, household dietary diversity and per capita monthly income were higher for adopters than non-adopters. However, as expected the GHG emissions and was lower for adopter compared to non-adopters of CSA practices. Although unexpected, the study revealed that non-adopters experienced higher value of livestock holding and household assets compared to adopters. A summary of the socioeconomic and demographic profile of the respondents also show that overall, 78% of the households were male headed households with a mean age of 47 years. About 92% were also married and with an average of 10 years education. The average household size was six people with an average of three adults and three children. However, the average per capita monthly income and expenditure were found to be Ksh. 4,217 and Ksh. 5,870 respectively. This is because most households often under report their income. On the other hand, the GHG emission was estimated at 140,000 Mt. In addition, it was also revealed that only 21% of the respondents agreed that the county government gets in touch with them on matters CSA practices while only 11% had received training on CSA practices. A description of the other variables classified for whole sample, adopters and non-adopters of CSA practices is presented in Table 4.

Table 4. Summary Statistics

	Whole Sample (n=1809)		Adopters (n=969)		Non-Adopters of CSA (n=840)	
Variable	mean	Sd	Mean	sd	Mean	Sd
Dependent Variables						
HDDS	5.609	1.886	5.862	2.108	5.317	1.541
Total value of livestock holding (millions)	1.064	9.880	1.014	5.419	1.123	13.28
Total value of HH assets (millions)	585.5	7448	1090	10151	2.919	38.26
Percapita Monthly Income	4217	13595	4690	17215	3672	7470
Per capita monthly expenditure	5870	5993	6396	6880	5264	4700
Average GHG Emission (‘000’ Mt)	140.0	188.8	125.0	176.7	157.2	200.6
Explanatory Variables						
1 if County has KCSAP	0.354	0.478	0.311	0.463	0.405	0.491
Age of HH head (years)	46.80	14.58	47.31	13.90	46.20	15.30
1 if HH sex is male	0.778	0.416	0.811	0.392	0.739	0.439
1 if HH head is married	0.919	1.731	1.005	2.334	0.819	0.385
HH number of children	2.888	1.986	2.720	1.891	3.082	2.075
HH size	6.307	2.560	6.140	2.461	6.500	2.659

1 if HH received input subsidy	0.233	0.423	0.247	0.431	0.217	0.412
1 if county contact on CSA	0.206	0.404	0.262	0.440	0.140	0.348
1 if HH member of local group	0.594	0.491	0.584	0.493	0.605	0.489
1 if HH head employed	0.744	0.437	0.817	0.387	0.658	0.475
1 if HH head own smartphone	0.521	0.500	0.535	0.499	0.505	0.500
1 if HH head has access to loan	0.539	0.499	0.613	0.487	0.454	0.498
1 if HH head is a native	0.745	0.436	0.768	0.422	0.719	0.450
HH head years of education	9.780	4.616	10.09	4.357	9.423	4.876
1 if HH trained on CSA	0.111	0.314	0.119	0.324	0.102	0.303
1 if HH is a fish farmer	0.601	0.490	0.684	0.465	0.505	0.500
1 if HH is livestock farmer	0.836	0.370	0.844	0.363	0.827	0.378
1 if HH crop farmer	0.897	0.304	0.971	0.168	0.812	0.391
1 if HH is mixed farmer	0.760	0.427	0.835	0.371	0.673	0.470
HH Monthly Income	20926	53024	24053	70192	17320	18703
1 if primary activity of HH is Agriculture	0.760	0.427	0.745	0.436	0.776	0.417
Number of Agric Extension visit	0.606	4.583	0.673	4.660	0.530	4.494
1 if HH experienced hailstorm	0.625	0.592	0.655	0.476	0.590	0.702
Distance to county office (km)	21.14	16.76	20.08	15.30	22.37	18.23
1 if HH experienced insuff rain	0.489	0.500	0.426	0.495	0.561	0.497
1 if HH was visited by agrix ext	0.172	0.377	0.235	0.424	0.0988	0.299
1 if HH has crop insurance	0.0431	0.203	0.0382	0.192	0.0488	0.216
1 if HH has livestock insurance	0.0398	0.196	0.0506	0.219	0.0274	0.163
1 if HH received Agric Infor	0.546	0.498	0.659	0.474	0.415	0.493
1 if HH received weather infor	0.643	0.479	0.745	0.436	0.525	0.500
HH land size (Acres)	14.66	186.3	3.122	8.990	27.96	272.7
1 if HH head heard of CSA	0.321	0.467	0.394	0.489	0.237	0.425
Distance to livestock market (km)	6.615	6.843	5.724	7.451	7.644	5.907
Distance to crop market (km)	4.885	12.99	4.197	4.256	5.678	18.49

The study also revealed that about 84% of the sampled households were livestock farmers, 90% crop farmers and 76% mixed farmers whereas only 6% practiced fish farming. A summary of the CSA practices adopted by farmers in the 22 counties is presented in Table 5. The results revealed that the predominant CSA crop management practices were: intercropping (79%); changing planting dates (75.3%) and drought resistant crops and crop varieties and crop rotation each at 68% and mostly dominated by male headed households. Predominant land management CSA practices included use of terraces (63.9%); use of live fence (59.7%); and planting trees on crop land (56.3%). The predominant farm risk reduction practices were mainly use of weather forecast (55.9%) and crop diversification (44.5%) which were dominated by male headed households. On the other hand, for soil and water conservation, practices the predominant practices included application of organic manure (62.7%); integration of legumes (60.9%); and efficient use of inorganic fertilizers (54.6%) which were as well dominated by male headed households. Lastly, livestock management practices were the least adopted despite over 83% of the households being livestock farmers. This shows the need to cascade more CSA practices aimed at the livestock sector. Overall, we found that predominant CSA practice was crop management practices revealing that most household tend to use the traditional CSA practices.

Table 5. Summary of climate smart agriculture practices

		Whole Sample (n=1809)		Male (n=1407)		Female (n=403)	
		Mean	Sd	Mean	Sd	mean	Sd
Crop Management Practices	Drought resistant crops	0.682	0.466	0.716	0.451	0.562	0.497
	Crop Rotation	0.677	0.468	0.706	0.456	0.575	0.495
	Changing planting dates	0.753	0.431	0.757	0.429	0.741	0.438
	Sequential cropping	0.300	0.458	0.291	0.455	0.328	0.470
	Multi season cropping	0.577	0.494	0.598	0.491	0.502	0.501
	Intercropping	0.790	0.407	0.814	0.389	0.709	0.455
Land management practices	Use of terraces	0.639	0.480	0.652	0.476	0.592	0.492
	Stone gabions	0.0962	0.295	0.0917	0.289	0.112	0.316
	Planting trees on crop land	0.563	0.496	0.576	0.494	0.517	0.500
	Use of live fences	0.597	0.491	0.629	0.483	0.485	0.500
	Adoption of cover crop	0.432	0.496	0.444	0.497	0.391	0.488
Farm risk reduction practices	Diversified crops	0.445	0.497	0.475	0.500	0.338	0.474
	Irrigation	0.189	0.392	0.190	0.392	0.187	0.390
	Use of weather forecast	0.559	0.497	0.601	0.490	0.415	0.493
	Insurance (livestock and crop)	0.350	0.477	0.362	0.481	0.308	0.462
Soil and water conservation practices	Planting food crops	0.402	0.490	0.416	0.493	0.351	0.478
	Mulching	0.364	0.481	0.370	0.483	0.343	0.475
	Rain and flood water	0.449	0.498	0.449	0.498	0.450	0.498
	Application of organic manure	0.627	0.484	0.665	0.472	0.495	0.501
	Integration of legumes	0.609	0.488	0.627	0.484	0.545	0.499
	Efficient use of inorganic	0.546	0.498	0.575	0.495	0.445	0.498
Livestock Management practices	Use of plastic silos	0.100	0.300	0.113	0.317	0.0547	0.228
	Use of Muskan milk containers	0.0929	0.290	0.101	0.301	0.0647	0.246
	Diversification of animal	0.189	0.391	0.199	0.399	0.152	0.359
	Improved livestock breeds	0.208	0.406	0.217	0.412	0.177	0.382
	Fodder banks	0.135	0.342	0.151	0.358	0.0821	0.275

An analysis by sex of household heads also revealed that males predominantly adopted most CSA practices. This could be due to the fact that although women are the ones who engage in farming, the farming decision and CSA practices to be adopted is mostly made by men in the households.

In addition, an analysis of the summary statistics based on agro-Ecological zones revealed that despite the significant differences across agro-ecological zones, the predominant CSA practices in all agro-ecological zones were crop management practices (see Table A4 and A5 in the annex). We also found that in all zones, the traditional practices such as intercropping, integration of legumes, application of organic manure still reined while the uptake of CSA livestock management practices were extremely low in all regions.

4.3 Descriptive Statistics

It is important to note that, adoption of CSA practices is voluntary and maybe based on self-selection. In addition, Table A1 revealed that households adopting CSA practices have systematically different characteristics from non-adopters of CSA practices. This could be the case since households may adopt CSA practices based on anticipated benefits, inert ability, level of knowledge on CSA and whether household has received training on CSA among other factors.

Unobserved factors may also influence household adoption of CSA practices as well as the outcome variables. Ignoring these factors may lead to biased and inconsistent estimates of the impact of adoption of CSA practices. Overall, the significant mean differences for some covariates (see Table A1 in the annex) suggest that observed outcomes for non-adopters of CSA may not provide good counterfactual for adopters of CSA.

4.4 Determinants of adoption of CSA practices

To identify the determinants of adoption of CSA practices, the study employed the probit model. Table 6 presents the probit model estimate results. The results revealed that in counties with the KCSAP project, households were less likely to adopt CSA practices. This could generally be due to rebellion by citizens or just negative attitude by the populace or perception on how national government utilizes the funds. This could also be attributed to the fact that KCSAP is implemented by national government hence little support from county government since they consider agriculture a devolved function. Another possible reason could be maybe based on the kind of CSA practices being promoted by KCSAP. On the other hand, the results revealed that adoption of CSA practices increases with age at a decreasing rate. This is because the youth are more knowledgeable and the physical strength which diminishes as they get old (Martey *et al.,* 2021). Similarly, the study revealed that male headed households were more likely to adopt CSA practices compared to female headed households. This is because investment in some of the CSA technologies could be labour and/or capital intensive which usually falls in the domain of employed males (Manda *et al.,* 2016). Males are also more likely to access information on CSA hence the high likelihood of adoption. This also support findings by Wekesa et al. 2018. Households are also less likely to adopt CSA practices with increase in household size. This is because some CSA practices may require resources which with more mouths to feed households may tend to implement some cost cutting measures. It was also more evident that crop farmers are more likely to adopt CSA practices similar to findings by McCord et al., (2015). This also explains the predominance of adoption of CSA practices inclined to crop management/farming.

Table 6. Determinants of adoption CSA practices

	(1)	(2)
VARIABLES	Coefficients	Marginal Effects
1 if County has KCSAP	-0.300***	-0.104***
	(0.0673)	(0.0230)
Age of HH head (years)	0.0331***	0.0115***
	(0.0123)	(0.00423)
Age^2 of HH head	-0.000335***	-0.000116***
	(0.000126)	(4.36e-05)
HH size	-0.0412***	-0.0143***
	(0.0127)	(0.00438)
1 if HH sex is male	0.148*	0.0512*
	(0.0789)	(0.0273)
1 if HH head is married	0.0564	0.0196
	(0.0349)	(0.0121)
1 if HH head own smartphone	-0.0777	-0.0270
	(0.0655)	(0.0227)
1 if HH received input subsidy	-0.0316	-0.0110
	(0.0787)	(0.0273)
1 if HH head is a native	0.0629	0.0218
	(0.0733)	(0.0254)
1 if HH crop farmer	1.127***	0.391***
	(0.124)	(0.0403)
1 if HH was visited by agric extension	0.622***	0.216***
	(0.0909)	(0.0304)
1 if county contact on CSA	0.327***	0.114***

	(0.0864)	(0.0297)
1 if HH trained on CSA	-0.156	-0.0543
	(0.106)	(0.0369)
1 if HH head heard of CSA	0.182**	0.0632**
	(0.0754)	(0.0260)
1 if HH experienced insuff rain	-0.182***	-0.0633***
	(0.0661)	(0.0228)
HH land size (Acres)	-0.000800	-0.000278
	(0.000543)	(0.000188)
Constant	-1.592***	
	(0.314)	
Observations	1,809	1,809
Adoption rate	53.4%	

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

In addition, the study revealed that households visited by agriculture extension officers, had heard of CSA and had been in contact with county government on CSA were more likely to adopt CSA practices reflecting the importance of creation of awareness on CSA practices. These findings lend support to the works of Mayaya et al. (2015) and McCord et al. (2015). However, it was also noted that households in counties that experience insufficient rainfall were less likely to adopt CSA practices maybe due to fear of losses in case rain fails. This could also be due to the fact that in areas with insufficient rainfall the main practices were livestock farming which had very few CSA practices adopted pertaining to livestock management. The overall adoption rate among smallholder farmers was estimated to be about 53% countrywide based on the estimates from the 22 sampled counties.

4.5 Factors Influencing Choice of CSA practices

The analysis was extended further by assessing factors influencing the choice of specific CSA practices among smallholder farmers. The CSA practices in Table 5 were condensed into the five groupings. The Kaiser-Meyer Olkin (KMO) measure of sampling adequacy revealed that crop management practices, land management practices, farm risk diversification, soil and water conservation, livestock management practices had an overall KMO measure of 0.67, 0.68, 0.59, 0.64 and 0.65 respectively allowing use of PCA. The study therefore classified households based on PC Scores with PC scores greater than zero as adopters of CSA and those with less than zero as non-adopters for each category and all categories grouped together. We then estimated a probit model to identify the factors influencing choice of the CSA practices based on the overall PC scores for all CSA practices. The results are presented in Table 7. Overall, the results revealed that adoption of crop management practices was highest followed by land management practices, farm risk reduction practices, soil conservation and lastly livestock management practices at 60.9%, 47.4%, 47.3%, 45.7% and 35.1% respectively.

Table 7. Factors influencing choice of CSA practices

VARIABLES	(1) Crop Management	(2) Land Management	(3) Farm Risk Reduction	(4) Soil and Water Conservation	(1) Livestock Management
1 if County has KCSAP	-0.166**	-0.164**	-0.371***	-0.303***	-0.0826
	(0.0698)	(0.0657)	(0.0676)	(0.0674)	(0.0680)
Age of HH head (years)	0.0169	0.00483	0.00171	0.0269**	0.0236*
	(0.0124)	(0.0121)	(0.0123)	(0.0125)	(0.0125)
Age^2 of HH head	-0.000146	6.45e-06	-5.00e-05	-0.00028**	-0.000237*
	(0.000128)	(0.000125)	(0.000127)	(0.000129)	(0.000129)
HH size	-0.000970	-0.0207*	-0.0227*	-0.0486***	-0.0240*
	(0.0136)	(0.0125)	(0.0130)	(0.0127)	(0.0134)
1 if HH sex is male	0.0121	0.298***	0.262***	0.127	0.439***
	(0.0892)	(0.0764)	(0.0887)	(0.0804)	(0.0824)
1 if HH head is married	0.419***	-0.0238	0.192**	-0.0706	-0.0107
	(0.0954)	(0.0202)	(0.0962)	(0.0464)	(0.0237)
1 if HH head own smartphone	0.0577	-0.189***	0.150**	-0.140**	0.320***
	(0.0694)	(0.0652)	(0.0666)	(0.0673)	(0.0674)
1 if HH received input subsidy	0.0122	-0.128*	-0.224***	0.291***	0.297***
	(0.0822)	(0.0768)	(0.0785)	(0.0769)	(0.0775)
1 if HH head is a native	-0.0634	0.0154	0.0821	0.119	0.178**
	(0.0768)	(0.0722)	(0.0740)	(0.0729)	(0.0745)
1 if HH crop farmer	1.144***	0.782***	0.670***	0.733***	0.337***
	(0.124)	(0.118)	(0.121)	(0.119)	(0.120)
1 if HH was visited by agric extension	0.417***	0.384***	0.531***	0.173**	-0.286***
	(0.0954)	(0.0870)	(0.0906)	(0.0884)	(0.0904)
1 if county contact on CSA	0.401***	0.130	-0.238***	0.356***	-0.0323
	(0.0919)	(0.0832)	(0.0856)	(0.0859)	(0.0844)
1 if HH trained on CSA	-0.417***	0.118	-0.194*	-0.478***	0.00823
	(0.109)	(0.103)	(0.107)	(0.105)	(0.105)
1 if HH head heard of CSA	0.249***	-0.182**	0.174**	0.0538	0.108
	(0.0796)	(0.0741)	(0.0760)	(0.0755)	(0.0756)
1 if HH experienced insuff rain	0.101	-0.113*	-0.354***	-0.0119	-0.273***

	(0.0688)	(0.0649)	(0.0665)	(0.0661)	(0.0667)
HH land size (Acres)	0.00127	-0.000955	-0.000762	-0.0101**	-0.000680
	(0.00378)	(0.000646)	(0.000634)	(0.00487)	(0.000744)
1 if HH head has access to loan	0.505***	0.173***	0.231***	0.212***	0.131*
	(0.0692)	(0.0661)	(0.0680)	(0.0678)	(0.0684)
1 if member of local group	-0.137**	0.00244	-0.219***	-0.263***	0.0138
	(0.0691)	(0.0657)	(0.0679)	(0.0671)	(0.0676)
Constant	-1.878***	-1.001***	-0.721**	-1.055***	-1.693***
	(0.318)	(0.306)	(0.312)	(0.316)	(0.321)
Observations	1,809	1,809	1,809	1,809	1,809
Adoption rate	60.9%	47.4%	47.3%	45.7%	35.1%

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The results show that in counties where the KCSAP project operates, households are less likely to adopt all the categories of CSA practices. This could be due to the negative perception of communities towards say any project initiated by government maybe as a protest mechanism. Male headed households are also more likely to adopt land management, farm risk reduction and livestock management practices. The married are also more likely to adopt crop and farm risk reduction practices. It was also revealed that the higher the household size the less likely are households to adopt the different CSA practices. However, households with smartphones are more likely to adopt farm risk reduction practices and livestock management practices but less likely to adopt land management and soil conservation practices. Households that received input subsidy were also less likely to adopt land management practices and farm risk reduction but more likely to adopt soil conservation and livestock management practices. The results also revealed that crop farmers were more likely adopt all the categories of CSA practices. Moreover, farmers who had been visited by agriculture extension officers were more likely to adopt crop management, land management, farm risk reduction and soil conservation practices but less likely to adopt livestock management practices.

The results also revealed that households that received communication from county government on CSA were more likely to adopt crop management and farm risk reduction. This implies that county government communication to households is very effective in promoting CSA. In addition, households that had heard of CSA were more likely to adopt crop management, farm risk reduction but less likely to adopt land management practices. As expected, access to loans was found to positively influence adoption of all categories of

CSA practices lending support to the works of Makate et al. (2019) and Mayaya et al (2015). This implies that adoption of CSA practices is hampered by limited funding. Membership to groups in the villages was also found to negatively influence CSA adoption. This could be due to household engaging in other group activities not necessarily farming.

In terms of climatic variables, the study revealed that households that had experienced insufficient rainfall in the past were less likely to adopt land management, farm risk reduction and livestock management practices. This could be because some farmers may be risk averse after facing some losses from agriculture in the past.

4.6 OLS Regression model estimates

The study first estimated the standard ordinary least square regression model as our naïve estimates, the results are as presented in Table A2 in the annex. The results revealed that holding other factors constant, adoption of CSA practices has a positive effect on food security, value of household assets, savings as proxied by value of livestock holding, per capita monthly expenditure and a negative effect on GHG emission as expected.

In addition, since adoption of CSA practices was not purely random, OLS may yield biased estimates, we extended the analysis further by estimating an IPW regression model to handle self-selection issues, Instrumental variable regression model and Lewbel's heteroscedasticity based instrumental variable model that uses internally generated instruments to address the endogeneity concerns.

4.7 Inverse probability Weighting regression model results

Given that adoption of CSA practices was not completely random, OLS estimates would lead to biased estimates. We first employed the IPW regression model to address the selectivity issues. However, the underlying assumptions of IPW must be met i.e. confoundedness and overlap. The results depicted sufficient overlap although there are few propensity scores closer to zero. This implies that the regions too close to zero or one will not be within the common support. The primary IPW estimates are presented in Table 8.

Table 8. Average Treatment Effect on the Treated estimates from IPW regression model results

Variables	Household Dietary Diversity (Food Security)	Value of Livestock Holding in millions (Savings)	Value of Household assets in millions	Per capita Monthly Expenditure	GHG Emission ("000" Mt)
CSA	0.192**	0.139	1095.696***	-216.660	-33.73***
	(0.095)	(0.384)	(324.071)	(287.318)	(9010.199)
Constant	5.530***	0.871**	2.463**	6188.157***	157.43***
	(0.069)	(0.344)	(1.114)	(249.033)	(6947.506)

Although the results in Table 8 could be sensitive to inclusion of additional covariates. the results revealed that there is evidence of treatment effect in agreement with the mean differences in Table A1. However, despite the sensitivity to choice of counterfactual, the direction as well as size of the program impacts may not be particularly sensitive to the inclusion of a broader set of covariates. The results confirmed that the impact of CSA adoption was significant and positive on household dietary diversity i.e., food security, value of household assets and significantly led to reduction in GHG emission.

4.8 Instrumental Variable regression Model Results

Since adoption of CSA practices could be potentially endogenous to the outcome variables, we first tested for endogeneity of CSA adoption. The control function approach19 was employed to test for endogeneity. The test revealed that CSA adoption was not endogenous to value of livestock holding as the null hypothesis of exogeneity is not rejected. However, the null hypothesis of exogeneity was rejected for GHG emission, Household dietary diversity, value of household assets and per capita monthly expenditure showing that adoption of CSA practices is endogenous to the four outcomes. This implies that we cannot proceed to estimate a standard OLS model for GHG emission, value of household assets, household dietary diversity and per capita monthly expenditure. We therefore proceeded to estimate an instrumental variable regression model to address the endogeneity concerns. The performance Statistics for the IV models is presented in Table A3. We first tested

[19] The approach is almost similar to the 2SLS approach but the only difference is that it allows for testing of endogeneity of CSA adoption. However, it hinges on the assumption of exogeneity of the instrument.

whether the excluded instruments are correlated with the endogenous regressors (under-identification). Based on Kleibergen-Paarp rk LM statistic (see Table A3 in the Annex), we reject the null hypothesis that the equations are under-identified at 1 % level of significance. The second step, we tested for weak identification since if excluded instruments are weakly correlated with the endogenous regressors, then the instruments may yield poor estimates. Using the Craig-Donald Wald F statistic, we reject the null of weak identification as shown by the large F statistic for all the outcomes.

The Hansen J statistic was also used to test for over-identification under the null hypothesis that the instruments are valid (i.e. uncorrelated with the error term and the excluded instruments are correctly excluded from the estimated equation). Under this test, we reject the null hypothesis that the instruments are valid for model for food security and value of livestock holding. These results show that the validity of over-identifying restrictions provides limited information on the ability of the instruments to identify parameters of interest. However, it is important to note that this is not a finite sample limitation of the test but just one of its intrinsic characteristics (Parente et al. 2012). According to Parente et al. (2012), the test checks the coherence of the instrument and not validity of the instruments. We can therefore still make inference based on the instrumental variable estimates.

The results were obtained using the ivreg2 Stata command for an extended instrumental variable regression model are presented in Table 9 for all the outcome measures to assess the robustness of IPW estimates.

Table 9. Instrumental variable regression Model Estimates

Variables	(1)	(2)	(3)	(5)	(6)
	Household Dietary Diversity (Food Security)	Value of Livestock Holding in millions (Savings)	Value of Household assets in millions	Per capita Monthly Expenditure	GHG Emission ("000" Mt)
1 if HH adopt CSA Practice	3.355*	8.890*	-713.1	9,155**	-1,892***
	(1.990)	(5.386)	(4,755)	(3,760)	(461.6)
Age of HH head (years)	-0.00642	-0.0431**	49.62***	6.077	2.227
	(0.00452)	(0.0180)	(17.64)	(11.20)	(1.653)
1 if HH sex is male	0.0452	-0.206	478.1	-258.7	116.1**
	(0.167)	(0.468)	(303.2)	(363.8)	(56.41)

1 if HH received input subsidy	0.184	1.871**	-605.0*	-25.52	-85.16
	(0.190)	(0.952)	(330.3)	(463.7)	(60.16)
1 if County has KCSAP	0.171	0.743	-572.9	-216.8	-266.4***
	(0.188)	(0.852)	(419.3)	(393.9)	(58.10)
HH head years of education	0.0948***	0.0558	242.6***	335.7***	-10.23*
	(0.0145)	(0.0541)	(70.83)	(45.10)	(5.425)
1 if county contact on CSA	0.0675	-0.628	-458.7	297.5	276.7***
	(0.329)	(0.919)	(714.7)	(663.5)	(92.33)
1 if HH head is married	-0.0533**	-0.170	32.24	-26.95	27.87***
	(0.0267)	(0.104)	(57.74)	(50.28)	(7.474)
1 if HH was visited by agric extension	-0.511	0.879	-961.0	-2,390**	432.6***
	(0.476)	(1.365)	(1,070)	(932.0)	(119.5)
1 if HH trained on CSA	0.460***	-0.947	-525.2*	-367.0	-112.7
	(0.173)	(0.705)	(299.1)	(449.5)	(69.19)
HH land size (Acres)	0.000484	0.00227*	-0.663	1.669**	-0.358***
	(0.000422)	(0.00123)	(1.054)	(0.809)	(0.101)
1 if HH member of local group	0.207	-0.370	706.3*	856.4**	-104.9*
	(0.178)	(0.677)	(410.5)	(418.1)	(55.72)
1 if HH crop farmer	-1.111*	-4.862	264.7	-1,351	561.2***
	(0.611)	(3.182)	(1,400)	(1,192)	(154.1)
1 if HH head own smartphone	0.506***	-0.703	597.4**	1,922***	-56.45
	(0.135)	(0.704)	(254.1)	(335.7)	(47.99)
Distance to livestock market (km)	0.00429	0.158**	111.6**	70.90*	-10.89**
	(0.0120)	(0.0643)	(44.42)	(42.59)	(5.315)
1 if HH fish farmer	-0.0156	-2.304**	-1,701**	-3,076***	139.9**
	(0.247)	(0.944)	(767.2)	(523.1)	(68.98)
1 if HH head employed	0.140		1,260*	8.467	272.3***
	(0.292)		(744.1)	(543.2)	(79.44)
1 if HH livestock farmer	-0.259		-640.2**	-2,608***	110.3*
	(0.191)		(322.3)	(694.6)	(65.71)
1 if HH experienced hailstorm		0.163			-10.71
		(0.217)			(39.07)
Constant	3.814***	2.628	-4,542***	1,330	322.2***
	(0.299)	(2.592)	(1,344)	(885.5)	(123.9)
Observations	1,809	1,809	1,809	1,809	1,809

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The results revealed that adoption of CSA practices had a significant and positive impact on household welfare as proxied by per capita expenditure, household food security and on household savings as proxied by total value of livestock holding. The results also showed that adoption of CSA practices had a negative impact on GHG emissions. Specifically, the results revealed that adopters of CSA practices experienced increase in household dietary diversity index by about 28 percentage points, increased household savings (value of livestock holdings) by about ksh. 9 million, increased per capita monthly expenditure by about Ksh. 9000 and reduced GHG emission by about 1,892 thousand metric tonnes holding other factors constant. This indicates that adoption of CSA practices by households meet the dual objective as envisioned. To assess the robustness of IV estimates and the plausibility of the instruments, the analysis was further extended by employing the Lewbel's heteroscedasticity based instrumental variable approach.

4.9 Lewbel's Heteroscedasticity based instrumental variable Results

Cameron et al. (2005) highlights the difficulty of finding suitable instruments that satisfies the two conditions of validity and that the instrument must be highly correlated with adoption of CSA technologies but uncorrelated with the error term in the regression model. Lewbel's Heteroscedasticity based instrumental variable approach (Lewbel 2012; and Baum et al., 2013) uses internally generated instruments to test and address the potential endogeneity of adoption of CSA on the outcome variables. This approach rules out the problem of identification of instruments that meets the strict conditions. The method estimates an instrumental variable regression model providing options to generate instruments and allows identification of structural parameters in regression models with endogeneity or mis-measured regressors in the absence of traditional information on external instruments (Lewbel 2012).

According to Baum et al. (2015), identification is achieved by having explanatory variables that are uncorrelated with the product of heteroskedastic errors which is a key feature of models where the correlations in the error term are due to unobserved common factor. This approach is therefore well applied when there are no external instruments or used to supplement weak external instruments to improve efficiency of the instrumental variable estimator (Lewbel 2012). We first tested whether the excluded instruments are correlated with the endogenous regressors (under-identification). Based on Anderson Canon LM statistic (see Table A7 in the Annex), we reject the null hypothesis that the equations are under-identified at 1 % level of significance. We also reject the null hypothesis of weak identification for all outcomes based on the Craig-Donald Wald F statistic. The Sargan statistic test for over-identification under the null hypothesis that the instruments are valid (i.e. uncorrelated with the error term and the excluded instruments are correctly excluded from the estimated equation). Under this test, we reject the null hypothesis that the instruments are valid for model for food security and value of livestock holding. These results show that the validity of over-identifying restrictions provides limited information on the ability of the instruments to identify parameters of interest.

Table A6 presents the results of the Lewbel's heteroscedasticity based instrumental variable approach. We present results for all the outcome variables including those that were exogenous like total value of livestock holding. Although the test for endogeneity revealed that OLS provides better estimates for total value of livestock holding, since the impact is consistent throughout. The discussion of the results will be based on the IV estimates and Lewbel's heteroscedasticity based instrumental variable results.

The results revealed that conditioned on a set of covariates, the results show that adoption of CSA has a statistically and economically significant positive impact on household dietary diversity as a measure of food security, household per capita monthly expenditure and total value of household assets. These findings lend support to the works of Fischer (2018), Amadu (2020), Kaumbutho et al. (2007), Pretty (1999), Altieri (1999), Mendola (2007), Bell et al., 2018, Brown et al., 2018, Habtewold et al. (2021), Ogada et al. (2020), Radeny et al. (2018), Asfaw (2016), Teklewold (2019), Wekesa et al. (2018), Fentie et al. (2019. The results also revealed that adoption of CSA has a significant impact on GHG emission reduction.

In addition, the results revealed that Male headed households were more likely to lead to increased GHG emission compared to their female counterparts. This is expected given that males are more often engaged in physically intensive activity hence the more emission. Households that had been visited by extension officers also experienced increased value of livestock holding but low value of household assets. This could be attributed to the fact that most households once exposed to different agricultural skills may decide to venture in livestock production as a means of savings rather than purchasing household assets. Similarly, households that received input subsidy were more likely to increase their savings as revealed by the increase in the value of livestock holding. This is because most farmers invest their income from farming in livestock especially in rural areas.

As expected, counties that have KCSAP project were found to experience reduced GHG emissions although with reduced per capita expenditure. This could be because of reduced economic activity and not necessarily due to adoption of CSA practices. As expected, the study revealed the higher the years of schooling the more likely the household is to experience food security, increased value of household assets, increased per capita expenditure and reduced GHG emission. This can be due to the fact that with more education there are more prospects or availability of better off farm income hence higher per capita expenditure and investment in household assets as well as purchase of required food for the household. Households that had received training on CSA also experienced increased food security, and reduced GHG emission.

The ownership of smart phone was also found to lead to increased food security as one can easily google information and lead to increase per capita expenditure. On the other hand, value of livestock holding and household assets was found to increase with increase in distance to livestock market but food security and GHG emission were found to reduce with increase in distance to livestock market. This shows that opportunity costs associated with distance matters. Households with household heads employed in off farm jobs also experience increased food security, per capita expenditure and value of household assets as well as GHG emissions. This can be attributed to increase of household income from off farm activities hence high purchasing power.

Although we expected positive spillover effects because of presence of KCSAP project in a county, the results depicted otherwise showing the need for a better approach in implementing national government projects at the county level.

Chapter five

5.0 Conclusion and Policy Recommendations

The study sought to assess the impact of CCAFS engagement at policy and household level and specifically assess to what extent CCAFS engagement contributed to the observed changes in terms of shaping policy and CSA coordination among others. From the key informant interviews at the national and county level, it was evident that most of climate change and climate smart agriculture practices have been mainstreamed into the national plans (Kenya Vision 2030 MTPs, the Big Four) and in most County Integrated Development Plans. This is also reflected in the indicator handbooks for tracking progress in implementation of the mentioned plans. The progress reports on implementation of the plans also revealed the same. For instance, second “Big Four” report revealed that 488,793 farmers across 33 counties were provided insurance coverage against a target of 500,000 households in 37 counties.

The study found that CCAFS interventions have led to development of a range of policies aimed at promoting CSA. In effect several counties have developed county specific policies and frameworks on climate change, some have established climate change units and climate change fund all aimed at promoting CSA. However, apart from the multi-stakeholder platforms, the coordination of CSA practices from the national government to the county government has been weak. This is despite CSA falling under Food and Nutrition Security, one of the pillars of the “Big Four”. This calls for a well-coordinated approach to ensure smooth flow of information from the national to the county level. From the KII and FGDs there is very little interaction from the national government through the counties to households unlike before devolution when extension officers used to walk from farm to farm promoting government programmes like CSAs at community level. At the moment the two levels of governments work in silos which may compromise the realization of CCAFS objectives.

Despite the challenges, it is important to note that most of the policies in place at the national level and county levels would not have been in place without CCAFS and other development partners such as FAO interventions. It was noted that despite most counties being unaware of CCAFS most tried to emulate what is happening at national level hence the establishment of climate change fund, climate change units and climate change policies in some of the counties. The study also found that within CIDPs most almost all counties sampled had programmes promoting CSAs at the local level. In effect several counties have been providing weather information, input subsidies, trained framers on CSA and also promoted CSA through various forums and visits by extension officers.

Further, the study revealed that the uptake of CSA practices is influenced by age and sex of household head. The uptake was also found to be influenced by presence of KCSAP project in the county, visits by agricultural extension officers, household size, whether a household had heard of CSA or not, whether the county government contacted households on CSA or not and whether a household had experienced insufficient rainfall. Crop farming households were also found to be more likely to adopt CSA practices. The overall rate of adoption of CSA practices among farmers in Kenya was found to be about 53 percent.

It was also found that rural households still continue to adopt the traditional CSA practices mainly: application of organic manure; intercropping; crop rotation changing planning dates; use of inorganic fertilizers; multi season crops; and use of live fences and terraces in all agro-ecological zones. The uptake of other approaches such as; irrigation, use of cover crops, crop and livestock insurance, use of muskan milk containers and plastic silos, was relatively low. The most predominant CSA practice in Kenya is therefore crop management practices followed by land management and soil and water conservation practices. In terms of gender, the study revealed that male headed households were more likely to adopt CSA practices compared to female headed households.

On the other hand, the choice of specific CSA practices among smallholder farmers was found to be influenced mainly by sex, household size, marital status and education of household head. The choice of CSA practices is also influenced by smartphone ownership, training on CSA, provision of input subsidy by counties, past experience of insufficient rains, contact by county on CSA, visit by agricultural extension officers, knowledge on CSA and whether a household is a crop farmer. Other factors that were found to influence the choice of CSA practices were membership to local groups and presence of KCSAP project in the county. The choices of the type of CSA practices were also mainly dominated by males. This implies that in male headed households most decision on farming matters are made by men.

Hence the need for increased sensitization of communities on the role of both genders in promoting CSA especially since agricultural activities in households are conducted by women.

Overall, the adoption of the various CSA practices as well as the choice of CSA practices show that although there are some trickle-down effects of policy interventions to the household level, it is rather indirect and still low since most farmers have stuck to old traditional practices. The communication by counties to households or training on CSA were found not to have any influence on overall uptake of CSA practices but had a significant influence on the choice of some specific CSA practices adopted by households.

In terms of impact of adoption of CSA practices at household level, all the three empirical approaches employed in the study revealed that uptake of CSA by smallholder households increased household welfare measured in terms of per capita monthly household expenditure by about Ksh. 9000, increase household savings (total value of livestock holding) by Ksh. 8.9 million, increased food security as proxied by household dietary diversity index by about 28 percentage points while it reduced GHG emission by about 1.9 million metric tonnes. This implied that adoption of CSA practices meets the dual objective of achieving food security/improving farmer welfare and combating the effects of climate change. This was also supported with findings from the FGDs and KII. Some of the unintended impacts are the innovations like in Homa Bay where sweet potato farmers formed a marketing CBO. Although it is difficult to explicitly identify the mechanism of transmission of the impact, the study revealed that communication of CSA practices to households by county governments, sensitization of households through barazas and trainings, provision of input subsisdy, provision of weather information had some effect. In addition, TV programmes like Shamba Shape Ups have also been instrumental.

In conclusion, we find that CSA has potential of improving welfare of smallholder farmers if they can adopt more CSA practices. There is need for counties to establish an effective means of communication with households based on the heterogenous nature of communities in terms of level of education and access to information. A key lesson from the study is that increased sensitization of communities through baraza’s TV and radio adverts could increase uptake of CSA practices and technologies. A coordinated and integrated engagement between county and national governments can improve household welfare and food security and reduce GHG emission through CSA. In addition, the study revealed that improvement of roads infrastructure could enhance access to various market centres hence improving livelihood of communities. The use of social groups and social media can easily promote CSA uptake since farmers tend to implement what they see happening with their fellow farmers i.e. peer learning.

In terms of policy recommendations, first, there is need for a well-coordinated and integrated approach to promotion of CSA practices from the national to county level. This is because the impact of policy interventions is still low especially from the national level to the grass roots. This calls for a change of approach of for instance bringing on board county representatives into the multistakeholder platform in an arrangement where the national government is also just a member. This is due to the fact that when most of these platforms are organized by national governments counties always feel they are being managed by the national government yet they are independent. The best entry point for such interventions would be Council of Governors and incorporating of political leadership through county assembly's forum and national assembly.

Although most of the CCAFS interventions at the national level are being felt in a way though little and indirectly, there is need for CCAFS to move a step further for instance by dealing with counties directly for policy implementation since agriculture is a devolved function. This is because in developing countries of which Kenya is not an exception very well thought out policies are developed but implementation is often a problem. This situation is made worse by the disconnect between national and devolved government which should be the best opportunities for trickling down of such interventions.

Policy makers with support from CCAFS could also consider county specific tailor-made interventions to promote CSA. Some counties also suggested that there is need for an act setting aside specific budget for agriculture in order to enhance uptake of CSA technologies in order to protect communities against the effect of climate change and vulnerability. To enhance uptake of agriculture and weather information, policy makers need to consider developing IEC products in local languages to be shared in local radio stations. To provide market opportunities, farmers need to be encouraged to engage in contract farming and joining farmer cooperatives to increase access to market opportunities for their produce and avoid brokers this would increase savings and increase assets as well as household consumption expenditure and food security.

There is also need for increased sensitization of farmers on the need to invest in CSA practices to cushion them against the risk of climate change and also increase adoption of modern CSA practices. The use of local radio station is critical in promoting CSAs as it has been effective in providing weather and agricultural information. Finally, the agricultural extension services need to be upscaled to increase reach of rural households by county government.

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Annex

Table A1: Descriptive Statistics

Variable	CSA Adopters		CSA Non Adopters		Mean Difference	
	Mean	**s.e**	**Mean**	**s.e**	**Mean**	**s.e**
Dependent variables						
Total value of livestock holding	1.01***	0.17	1.12**	0.46	0.11	0.47
Per capita monthly expenditure	6395.71***	221.01	5263.72***	162.18	-1131.98***	281.33
Percapita Monthly Income	4690.09***	553.04	3671.51***	257.73	-1018.57	640.64
Total value of HH assets (millions)	1090.43***	326.10	2.92	1.32**	-1078.52***	350.26
HDD	5.86***	0.068	5.32***	0.053	-0.545***	0.088
Average GHG Emission (“000”Mt)	125.04***	5.68	157.22***	6.921	32.178***	8.87
Explanatory variables						
Age of HH head (years)	47.31***	0.45	46.20***	0.53	-1.10	0.69
HH sex	0.81***	0.01	0.74***	0.02	-0.07***	0.02
1 if HH head is married	1.00***	0.07	0.82***	0.01	-0.19**	0.08
HH head years of education	10.09***	0.14	9.42***	0.17	-0.67***	0.21
HH number of children	2.72***	0.06	3.08***	0.07	0.36***	0.09
HH size	6.14***	0.08	6.50***	0.09	0.36***	0.12
1 if member of local group	0.58***	0.02	0.60***	0.02	0.02	0.02
1 if HH head employed	0.82***	0.01	0.66***	0.02	-0.16***	0.02
1 if HH head own smartphone	0.53***	0.02	0.50***	0.02	-0.03	0.02
1 if HH head has access to loan	0.61***	0.02	0.45***	0.02	-0.16***	0.02
Amount of credit received	109280***	8843.93	104748***	5208	-4632	10665
1 if HH has crop insurance	0.04***	0.01	0.05***	0.01	0.01	0.01
1 if HH has livestock insurance	0.05***	0.01	0.03***	0.01	-0.02**	0.01
1 if HH has woodlot	0.29***	0.01	0.18**	0.01	-0.10***	0.02
1 if HH received Agric Information	0.66***	0.02	0.42***	0.02	-0.24***	0.02
1 if HH received weather information	0.74***	0.01	0.53***	0.02	-0.22***	0.02
1 if HH was visited by agric extension	0.24***	0.01	0.10***	0.01	-0.14***	0.02
1 if HH received input subsidy	0.25***	0.01	0.22***	0.01	-0.03	0.2
1 if HH receive insurance subsidy	0.10***	0.01	0.06***	0.01	-0.04***	0.01
1 if county contact on CSA	0.26***	0.01	0.14***	0.01	-0.12***	0.02
1 if HH received market information	0.67***	0.02	0.32***	0.02	-0.35***	0.02
1 if grew crops last season	0.95***	0.01	0.72***	0.02	-0.24***	0.02
HH land size (Acres)	3.12***	0.29	27.96***	9.41	24.84***	8.77
1 if HH head is a native	0.77***	0.01	0.72***	0.02	-0.05**	0.02
1 if HH head heard of CSA	0.39***	0.02	0.24***	0.01	-0.18***	0.02
1 if HH trained on CSA	0.12***	0.01	0.10***	0.01	-0.02***	0.01
Distance to forest(km)	21.71***	0.67	22.18***	1.05	0.47	1.21
Distance to school (km)	7.77***	1.65	6.70***	1.52	-1.06	2.27
Distance to livestock markt (km)	5.72***	0.24	7.64***	0.20	1.92***	0.32
Distance to crop market (km)	4.20***	0.14	5.68***	0.64	1.48**	0.61
Distance to tarmac road (km)	6.59***	0.48	10.23***	1.66	3.63**	1.63
Distance to agrovet (km)	4.53***	0.19	8.80***	0.45	4.27***	0.47

Table A2: OLS Regression model results

VARIABLES	(1) Household Dietary	(2) Value of Livestock	(3) Value of Household	(4) Per capita Monthly	(5) GHG Emission

	Diversity (Food Security)	Holding in millions (Savings)	assets in millions	Expenditure	(Mt)
1 if HH adopt CSA Practice	0.299**	1.015*	1,160**	549.6*	-39.47*
	(0.134)	(0.502)	(459.4)	(298.3)	(20.64)
1 if County has KCSAP	-0.164	0.515	-548.5	44.31	-114.0
	(0.109)	(0.617)	(507.2)	(506.2)	(73.34)
1 if HH head is married	-0.0116	-0.110	5.941	20.95	3.232
	(0.0109)	(0.0927)	(15.55)	(29.41)	(2.692)
1 if HH sex is male	0.182	0.380	-6.657	629.7	25.83
	(0.154)	(0.309)	(131.2)	(452.2)	(30.39)
Age of HH head (years)	0.00582	-0.175	27.46	87.60	-0.0600
	(0.0240)	(0.130)	(75.97)	(87.32)	(1.505)
Age^2 of HH head	-0.000128	0.00127	0.195	-0.499	-0.000527
	(0.000236)	(0.00116)	(0.755)	(0.861)	(0.0176)
HH head years of education	0.0958***	-0.0210	271.2**	251.7***	-3.938
	(0.0106)	(0.0663)	(111.1)	(55.65)	(4.553)
HH number of children	-0.0610*	-0.0838	-90.97*	-171.5	4.390
	(0.0341)	(0.128)	(47.75)	(168.6)	(6.108)
HH size	0.0348	0.111		-675.6***	6.763
	(0.0384)	(0.101)		(170.4)	(4.134)
1 if HH head is a native		0.697**	578.4	-112.1	-48.04*
		(0.256)	(384.2)	(318.3)	(24.68)
1 if HH have livestock insurance		-0.545		-1,263***	
		(0.556)		(401.6)	
1 if HH was visited by agric extension		2.215			14.45
		(1.424)			(12.68)
Distance to livestock market (km)	-0.0169	0.117		29.19	-1.381*
	(0.0156)	(0.0827)		(44.11)	(0.772)
Distance to county HQ	0.00406	0.0143*	34.44		
	(0.00396)	(0.00789)	(25.98)		
Distance to tarmac road (km)	1.86e-06	-0.0103*	-1.737	9.760*	
	(0.00168)	(0.00567)	(3.142)	(5.244)	
IntrCSA2		-6.060		-1,985	21.37
		(3.849)		(1,443)	(26.23)
1 if HH head own smartphone	0.384*	-0.964	241.3	1,583***	26.46*
	(0.215)	(0.624)	(172.2)	(418.7)	(14.26)
HH land size (Acres)	-0.000138***	0.000578**		-1.027***	0.0331
	(4.26e-05)	(0.000255)		(0.146)	(0.0239)
1 if county contact on CSA	0.652***	5.045	-1,041**	2,204**	2.021
	(0.177)	(3.663)	(468.6)	(910.3)	(17.46)
1 if HH head has access to loan	0.188*	-0.198	643.4**	2,253***	-46.93*
	(0.0907)	(0.429)	(272.4)	(361.3)	(25.99)
Number of Extension Visits	0.00473			38.97**	1.648
	(0.00638)			(18.28)	(2.097)
1 if HH received input subsidy			-467.2		
			(309.4)		
1 if member of local group			711.4*		
			(412.1)		
1 if HH head employed			418.4		
			(256.1)		
1 if HH trained on CSA			-871.8**		

			(407.3)		
1 if HH fish farmer			-1,873***		
			(575.9)		
1 if HH livestock farmer			-450.4*		
			(245.8)		
1 if HH experienced hailstorm				-925.2**	
				(400.9)	
Constant	4.019***	3.567	-4,415	2,661	214.8**
	(0.801)	(3.766)	(3,233)	(2,403)	(89.57)
Observations	1,809	1,809	1,809	1,809	1,809
R-squared	0.157	0.039	0.066	0.260	0.142

Cluster Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A3: Performance Statistics of IV models

Test	**Household Dietary Diversity (Food Security)**	Value of Livestock Holding in millions (Savings)	Value of Household assets in millions	Per capita Monthly Expenditure	GHG Emission ("000" Mt)
Under-identification test (Kleibergen-Paap rk LM statistic)	5.510	8.882	16.456	16.456	16.562
Chi-sq (24) p-val	0.0189	0.003	0.000	0.000	0.000
Weak identification test (Cragg-Donald Wald F statistic)	5.579	9.078	7.950	7.950	8.039
Hansen J statistic (Overidentification test)	0.000	0.000	0.779	0.225	0.779

Table A4: Summary of the CSA practices by Agro-Ecological Zones (AEZ)

Group	**CSA Practices**	**Upper Highlands**			**Upper Midlands**			**Lowland Highlands**		
		N	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Me**	**SD**
Crop Management Practices	Drought resistant crops	382	0.780	0.41	347	0.573	0.49	168	0.52	0.50
	Crop Rotation	382	0.736	0.44	347	0.749	0.43	168	0.60	0.49
	Changing planting dates	382	0.866	0.34	347	0.680	0.46	168	0.66	0.47
	Sequential cropping	382	0.448	0.49	347	0.291	0.45	168	0.23	0.42
	Multi season cropping	382	0.586	0.49	347	0.591	0.49	168	0.56	0.49
	Intercropping	382	0.851	0.35	347	0.824	0.38	168	0.73	0.44
Land Management Practices	Use of terraces	382	0.565	0.49	347	0.755	0.43	168	0.4	0.499
	Stone gabions	382	0.060	0.23	347	0.179	0.38	168	0.0	0.258
	Planting trees on crop land	382	0.545	0.49	347	0.640	0.48	168	0.4	0.501
	Use of live fences	382	0.615	0.48	347	0.545	0.49	168	0.4	0.495
	Adoption of cover crop	382	0.403	0.49	347	0.553	0.49	168	0.3	0.461
Farm risk reduction practices	Diversified crops	382	0.361	0.48	347	0.533	0.50	168	0.3	0.477
	Irrigation	382	0.183	0.38	347	0.219	0.41	168	0.1	0.389
	Use of weather forecast	382	0.602	0.49	347	0.493	0.50	168	0.4	0.499
	Insurance (livestock and crop)	382	0.385	0.48	347	0.357	0.48	168	0.2	0.407
Soil and water conservation practices	Planting food crops	382	0.432	0.49	347	0.473	0.50	168	0.2	0.450
	Mulching	382	0.408	0.49	347	0.476	0.50	168	0.3	0.461
	Rain and flood water harvesting	382	0.495	0.50	347	0.524	0.50	168	0.4	0.495
	Application of organic manure	382	0.550	0.49	347	0.651	0.47	168	0.6	0.481
	Integration of legumes	382	0.709	0.45	347	0.631	0.48	168	0.4	0.501
	Efficient use of inorganic fertilizers	382	0.563	0.49	347	0.608	0.48	168	0.5	0.501
Livestock Management practices	Use of plastic silos	382	0.131	0.33	347	0.133	0.34	168	0.0	0.286
	Use of Muskan milk containers	382	0.113	0.31	347	0.0865	0.28	168	0.1	0.363
	Diversification of animal breeds	382	0.236	0.42	347	0.320	0.46	168	0.1	0.398

	Improved livestock breeds	382	0.217	0.41	347	0.354	0.47	168	0.2	0.438
	Fodder banks	382	0.123	0.32	347	0.233	0.42	168	0.1	0.310

Table A5: Summary of CSA practices by Agro-Ecological Zones

Group	CSA Practices	Lowlands Midlands			Inland Lowlands			Coastal lowlands		
		N	Mean	SD	N	Mean	SD	N	Mean	SD
Crop Management Practices	Drought resistant crops	559	0.828	0.377	180	0.539	0.500	173	0.514	0.501
	Crop Rotation	559	0.732	0.443	180	0.594	0.492	173	0.387	0.489
	Changing planting dates	559	0.846	0.361	180	0.533	0.500	173	0.671	0.471
	Sequential cropping	559	0.297	0.457	180	0.289	0.455	173	0.0751	0.264
	Multi season cropping	559	0.617	0.487	180	0.472	0.501	173	0.520	0.501
	Intercropping	559	0.834	0.373	180	0.700	0.460	173	0.601	0.491
Land Management Practices	Use of terraces	559	0.757	0.429	180	0.522	0.501	173	0.497	0.501
	Stone gabions	559	0.0877	0.283	180	0.100	0.301	173	0.0578	0.234
	Planting trees on crop	559	0.619	0.486	180	0.439	0.498	173	0.491	0.501
	Use of live fences	559	0.725	0.447	180	0.439	0.498	173	0.584	0.494
	Adoption of cover crop	559	0.496	0.500	180	0.350	0.478	173	0.260	0.440
Farm risk reduction practices	Diversified crops	559	0.572	0.495	180	0.339	0.475	173	0.249	0.433
	Irrigation	559	0.182	0.387	180	0.167	0.374	173	0.191	0.394
	Use of weather forecast	559	0.669	0.471	180	0.367	0.483	173	0.555	0.498
	Insurance (livestock and	559	0.420	0.494	180	0.222	0.417	173	0.306	0.462
Soil and water conservation practices	Planting food crops	559	0.422	0.494	180	0.306	0.462	173	0.347	0.477
	Mulching	559	0.351	0.478	180	0.328	0.471	173	0.179	0.385
	Rain and flood water	559	0.454	0.498	180	0.361	0.482	173	0.301	0.460
	Application of organic	559	0.708	0.455	180	0.450	0.499	173	0.659	0.475
	Integration of legumes	559	0.683	0.466	180	0.433	0.497	173	0.399	0.491
	Efficient use of inorganic	559	0.592	0.492	180	0.439	0.498	173	0.370	0.484
Livestock Management practices	Use of plastic silos	559	0.0948	0.293	180	0.0667	0.250	173	0.0289	0.168
	Use of Muskan milk	559	0.0680	0.252	180	0.0667	0.250	173	0.110	0.314
	Diversification of animal	559	0.104	0.305	180	0.194	0.397	173	0.0809	0.274
	Improved livestock	559	0.148	0.356	180	0.144	0.353	173	0.104	0.306
	Fodder banks	559	0.132	0.339	180	0.0667	0.250	173	0.0751	0.264

Table A6: Lewbel's Heteroscedasticity Based Instrumental Variable Results

Variables	(1) Household Dietary Diversity (Food Security)	(2) Value of Livestock Holding in millions (Savings)	(3) Value of Household assets in millions	(4) Per capita Monthly Expenditure	(5) GHG Emission ("000" Mt)
1 if HH adopt CSA Practice	0.273*	1.171	863.0	959.8**	-35.70**
	(0.148)	(0.813)	(618.8)	(474.6)	(15.22)
Age of HH head (years)	-0.00272	-0.0368**	47.73***	15.92*	-0.0189
	(0.00297)	(0.0166)	(12.45)	(9.552)	(0.310)
1 if HH sex is male	0.209**	0.324	394.6	175.6	17.92*
	(0.103)	(0.580)	(429.8)	(329.6)	(10.61)
1 if HH received input subsidy	0.00473	1.493***	-513.2	-502.9	23.17**
	(0.102)	(0.577)	(427.8)	(328.1)	(10.57)
1 if County has KCSAP	-0.0601	0.195	-454.5	-832.2***	-127.2***
	(0.0926)	(0.525)	(387.9)	(297.5)	(9.583)
HH head years of education	0.0852***	0.0379	247.5***	310.1***	-4.397***

	(0.00973)	(0.0549)	(40.78)	(31.28)	(1.008)
1 if county contact on CSA	0.529***	0.586	-694.7	1,525***	-1.124
	(0.112)	(0.633)	(469.1)	(359.8)	(11.58)
1 if HH head is married	-0.0151	-0.0812	12.71	74.59	4.846**
	(0.0235)	(0.133)	(98.60)	(75.62)	(2.433)
1 if HH was visited by agric extension	0.164	2.510***	-1,306***	-594.3	25.50**
	(0.120)	(0.678)	(502.8)	(385.6)	(12.43)
1 if HH trained on CSA	0.330**	-1.211	-458.9	-712.1	-34.96**
	(0.135)	(0.765)	(566.1)	(434.2)	(14.00)
HH land size (Acres)	-0.000167	0.000750	-0.331	-0.0604	0.0336
	(0.000221)	(0.00125)	(0.927)	(0.711)	(0.0229)
1 if HH member of local group	-0.00234	-0.761	813.3**	300.0	21.15**
	(0.0883)	(0.494)	(370.0)	(283.7)	(9.128)
1 if HH crop farmer	-0.182	-2.260**	-210.3	1,119**	0.848
	(0.155)	(0.882)	(648.9)	(497.6)	(16.16)
1 if HH head own smartphone	0.392***	-0.869*	656.0*	1,618***	12.19
	(0.0891)	(0.504)	(373.4)	(286.4)	(9.260)
Distance to livestock market (km)	-0.0116*	0.110***	119.7***	28.73	-1.327**
	(0.00627)	(0.0351)	(26.26)	(20.14)	(0.648)
1 if HH fish farmer	0.308***	-1.482***	-1,867***	-2,216***	-54.83***
	(0.0953)	(0.537)	(399.4)	(306.3)	(9.856)
1 if HH livestock farmer	-0.0920		-725.6	-2,164***	9.723
	(0.115)		(481.2)	(369.0)	(11.87)
1 if HH head employed	0.545***		1,053**	1,085***	28.12***
	(0.104)		(434.3)	(333.1)	(10.75)
1 if HH experienced hailstorm		0.213			-7.518
		(0.404)			(7.378)
Constant	3.982***	3.733***	-4,628***	1,775**	221.3***
	(0.226)	(1.223)	(945.2)	(724.9)	(23.32)
Observations	1,809	1,809	1,809	1,809	1,809
R-squared	0.176	0.033	0.072	0.157	0.121

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A7: Performance Statistics of Lewbel's Heteroscedasticity based IV approach

Test	Household Dietary Diversity (Food Security)	Value of Livestock Holding in millions (Savings)	Value of Household assets in millions	Per capita Monthly Expenditure	GHG Emission ("000" Mt)
Anderson Canon. Corr. LM Statistic	644.281	675.182	644.281	644.281	648.133
Chi-sq (24) p-val	0.000	0.000	0.000	0.000	0.000
Weak identification test (Cragg-Donald Wald F statistic)	57.724	66.100	57.724	57.724	54.963
Sargan statistic (over-identification test of all instruments	75.324	82.050	169.218	60.441	40.418
Chi-sq (24) p-val	0.000	0.000	0.000	0.000	0.001

Annex B1: Lewbel's Heteroscedasticity based Instrumental Variable Approach

The IV approach seeks to address challenges in employing standard IV methods employed in linear regression models, e.g. $Y = X\beta + \mu$, where we experience violations of the zero conditional mean assumption$E[\mu|X] = 0$. Such IV models rely on availability of a suitable instruments to identify the model via exclusion restrictions. The instruments Z subsequently has to satisfy the following conditions: Orthogonality condition i.e. $E[\mu|X] = 0$; must be correlated with the X's; and properly excluded from the model, so that they only affect the outcome variable indirectly. The greatest challenge therefore in IV estimation is getting instruments which satisfy the three conditions concurrently. Lewbel's Heteroscedasticity Based Instrumental variable approach therefore comes in handy to identify structural parameters in regression models with endogenous or mis measured regressors in the absence of traditional identifying information such as external instruments or repeated measurements (see Lewbel et al., 2012). We therefore employed Lewbel's Heteroscedasticity based method to assess the robustness of IV estimates.

Analytical Framework

Following Lewbel et al., (2012) consider observed endogenous variables Y_1 and Y_2, and a vector of observed exogenous regresors X, and $\varepsilon = (\varepsilon_1, \varepsilon_2)$ is unobserved error processes. We consider the following structural model

$$Y_1 = X_0\beta + Y_2\gamma_1 + \varepsilon_1$$
$$Y_2 = X_0\beta + Y_1\gamma_2 + \varepsilon_2$$

This system is triangular when $\gamma_2 = 0$ (or with renumbering, when $\gamma_1 = 0$). Otherwise it is fully simultaneous. The errors $\varepsilon_1, \varepsilon_2$ may be correlated with each other. If the exogeneity assumption $E(\varepsilon X) = 0$ holds, the reduced form is identified, but in the absence of identifying restrictions, the structural parameters are not identified. These restrictions often involve setting certain elements of β_1 or β_2 to zero which makes instruments available[20].

[20] Identification in Lewbel's approach is achieved by *restricting* correlations of $\varepsilon\varepsilon'$ with X. This relies upon higher moments and is likely to be less reliable than identification based on coefficient zero restrictions. However, in the absence of plausible identifying restrictions, this approach may be the only reasonable strategy (Lewbel et al.2012).

The parameters of the structural model will remain unidentified under the standard homoscedasticity assumption: that $E(\varepsilon\varepsilon'|X)$ is a matrix of constants. However, in the presence of heteroscedasticity related to at least some elements of X, identification can be achieved.

In a fully simultaneous system, assuming that $cov\left(X, \varepsilon_j^2\right) \neq 0$: $j = 1; 2$ and $cov\ (Z, \varepsilon_1\varepsilon_2) = 0$ for observed Z will identify the structural parameters. Note that Z may be a subset of X, so no information outside the model specified above is required. The key assumption that $cov\ (Z, \varepsilon_1\varepsilon_2) = 0$ will automatically be satisfied if the mean zero error processes are conditionally independent: $\varepsilon_1 \perp \varepsilon_2 | Z = 0$. However, this independence is not strictly necessary.

This approach is crucial especially where there is some evidence of spill-over-effects among the control groups. Research has also shown that failure to address spill-over effects can lead to under or overestimation of the impact (Abadie et al., 2002).